Pre-training Models

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Outline

- Overview of pre-training
- Taxonomy of pre-training: context vs contrast
- More discussion about pre-training
- Summary

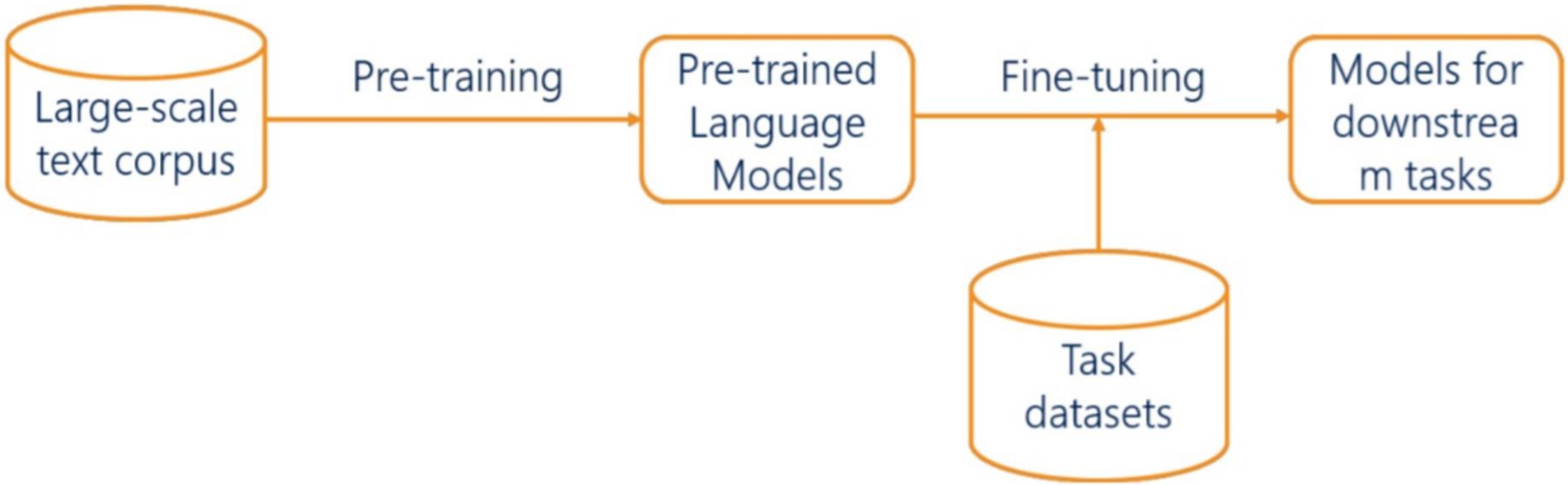
Pre-training

- What is pre-training?
  - The training in advance of standard training
- Why pre-training?
  - The standard training (data/model size) is not enough
- What to learn in pre-training?
  - Representation learning: more general, self-supervised
  - Task learning: more task specific, supervised
- When and where to apply pre-training?
  - Any tasks that data/model size are not enough
  - NLP, CV, Speech, and more

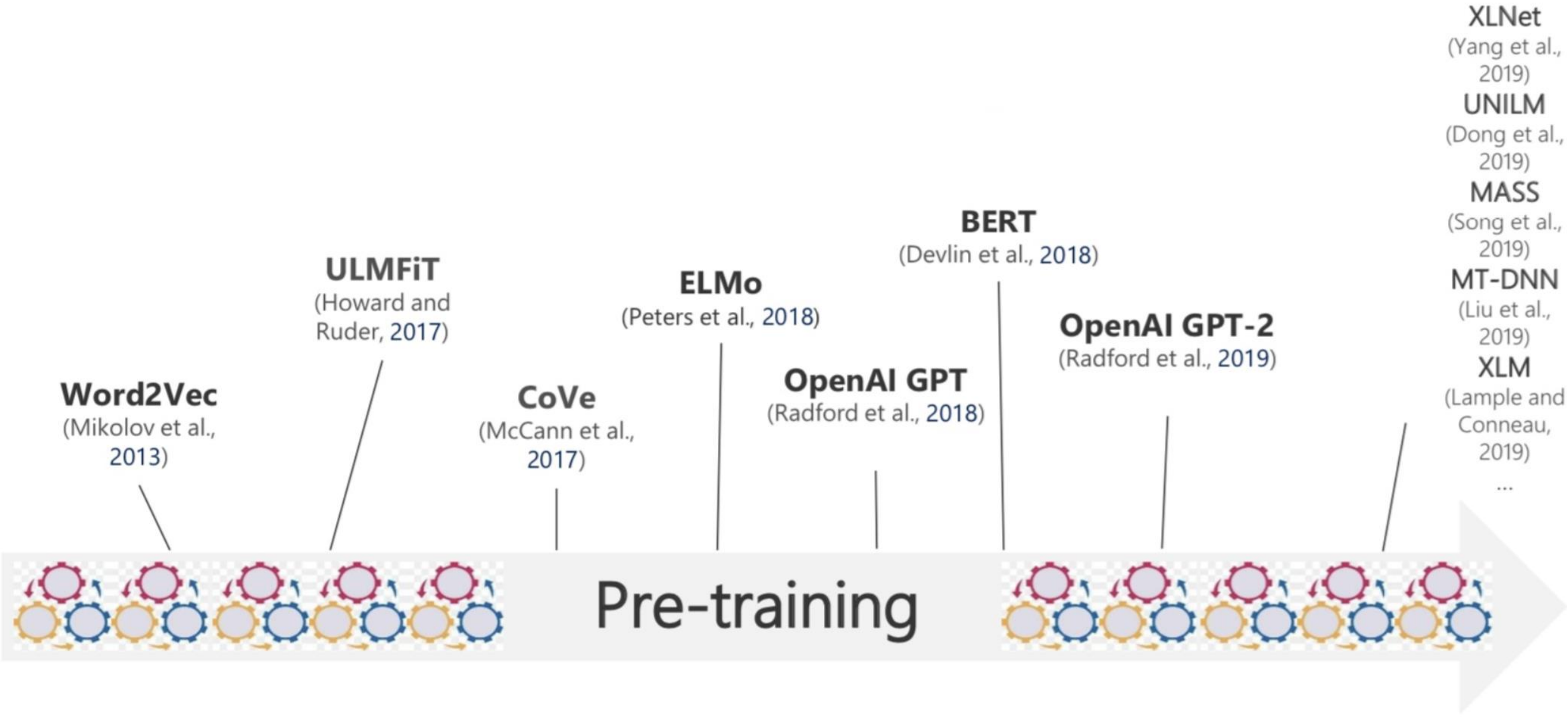
- **How to learn in pre-training?**

Pre-training in NLP

- Pre-training + Fine-tuning, a new paradigm of NLP



Pre-training in NLP



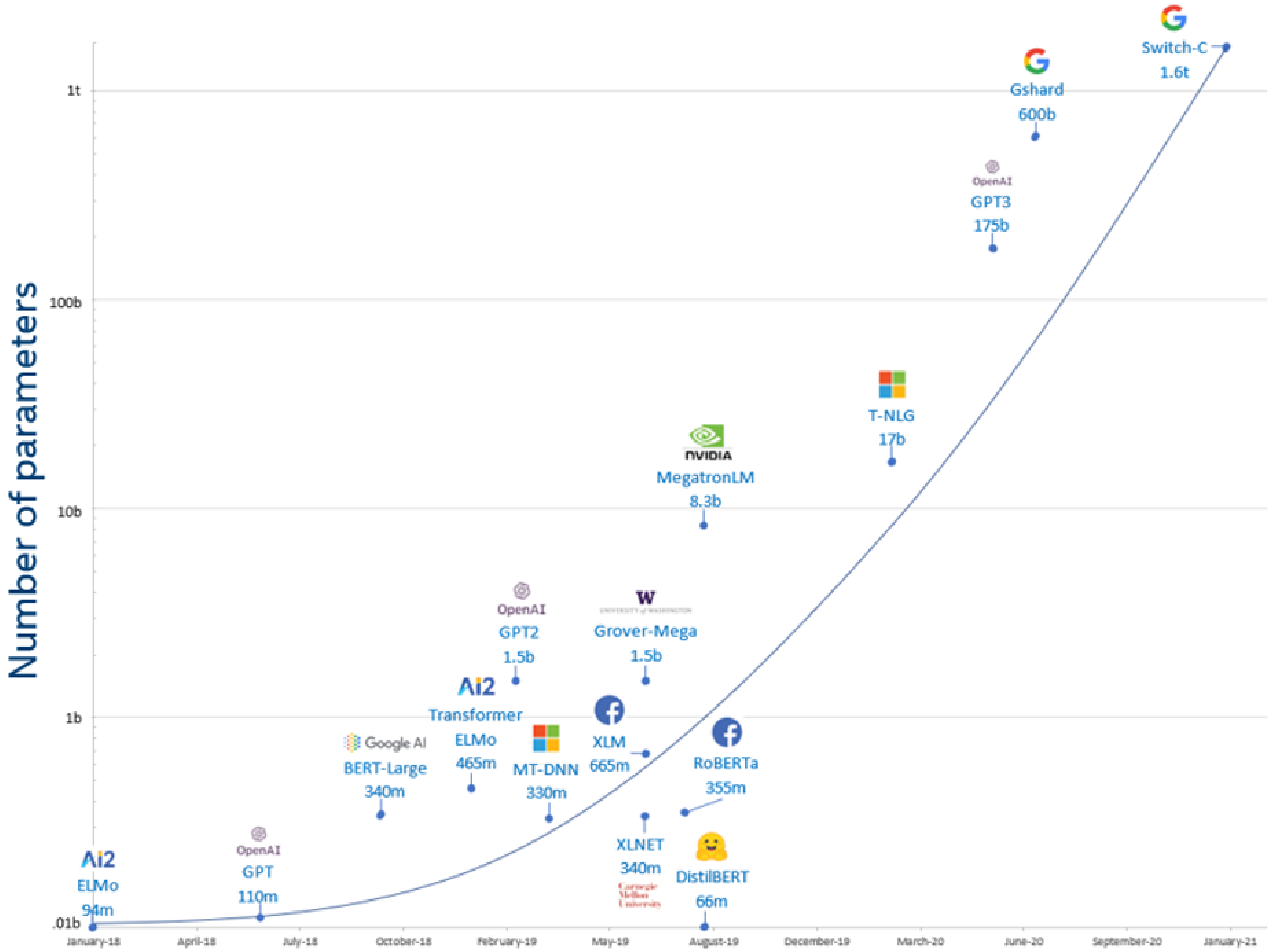
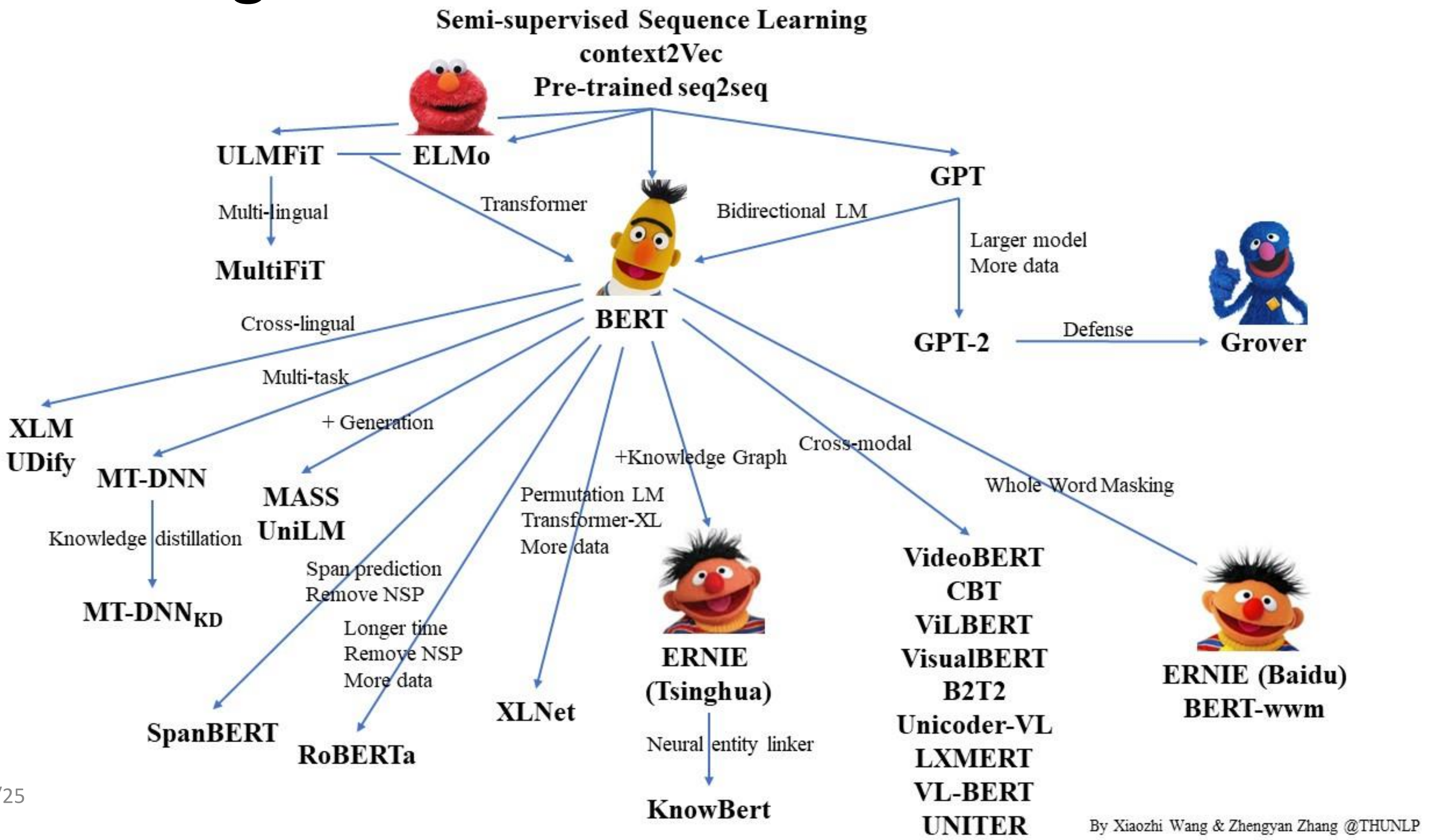
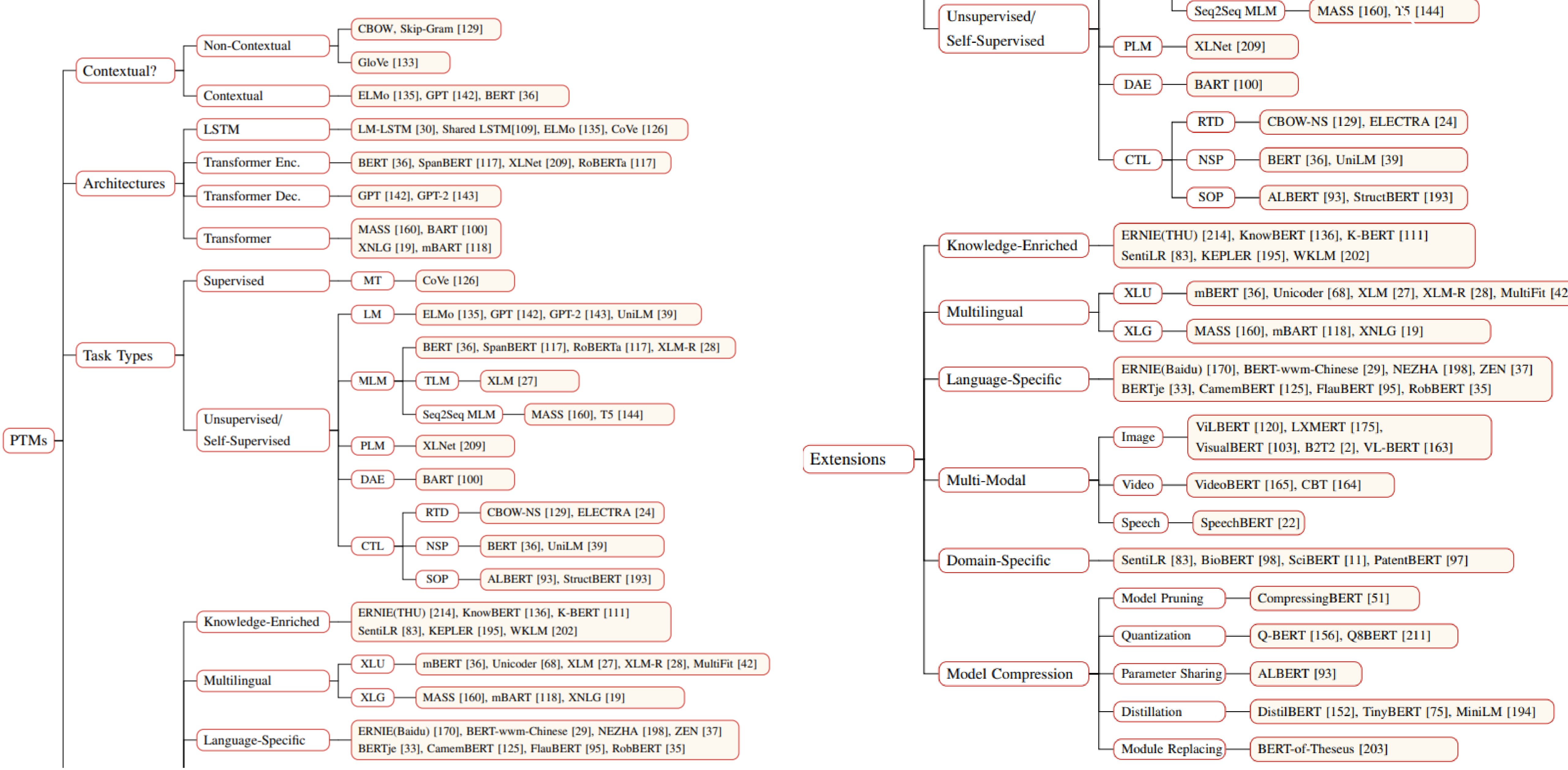


Figure 1: Exponential growth of number of parameters in DL models

Pre-training in NLP




PTMs
Contextual?
Non-Contextual
CBOW, Skip-Gram [129]
GloVe [133]
Contextual
ELMo [135], GPT [142], BERT [36]
Architectures
LSTM
LM-LSTM [30], Shared LSTM[109], ELMo [135], CoVe [126]
Transformer Enc.
BERT [36], SpanBERT [117], XLNet [209], RoBERTa [117]
Transformer Dec.
GPT [142], GPT-2 [143]
Transformer
MASS [160], BART [100]
XNLG [19], mBART [118]
Task Types
Supervised
MT
CoVe [126]
Unsupervised/
Self-Supervised
LM
ELMo [135], GPT [142], GPT-2 [143], UniLM [39]
MLM
BERT [36], SpanBERT [117], RoBERTa [117], XLM-R [28]
TLM
XLM [27]
Seq2Seq MLM
MASS [160], T5 [144]
PLM
XLNet [209]
DAE
BART [100]
CTL
RTD
CBOW-NS [129], ELECTRA [24]
NSP
BERT [36], UniLM [39]
SOP
ALBERT [93], StructBERT [193]
Knowledge-Enriched
ERNIE(THU) [214], KnowBERT [136], K-BERT [111]
SentiLR [83], KEPLER [195], WKLM [202]
Multilingual
XLU
mBERT [36], Unicoder [68], XLM [27], XLM-R [28], MultiFit [42]
XLG
MASS [160], mBART [118], XNLG [19]
Language-Specific
ERNIE(Baidu) [170], BERT-wwm-Chinese [29], NEZHA [198], ZEN [37]
BERTje [33], CamemBERT [125], FlauBERT [95], RobBERT [35]
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Extensions
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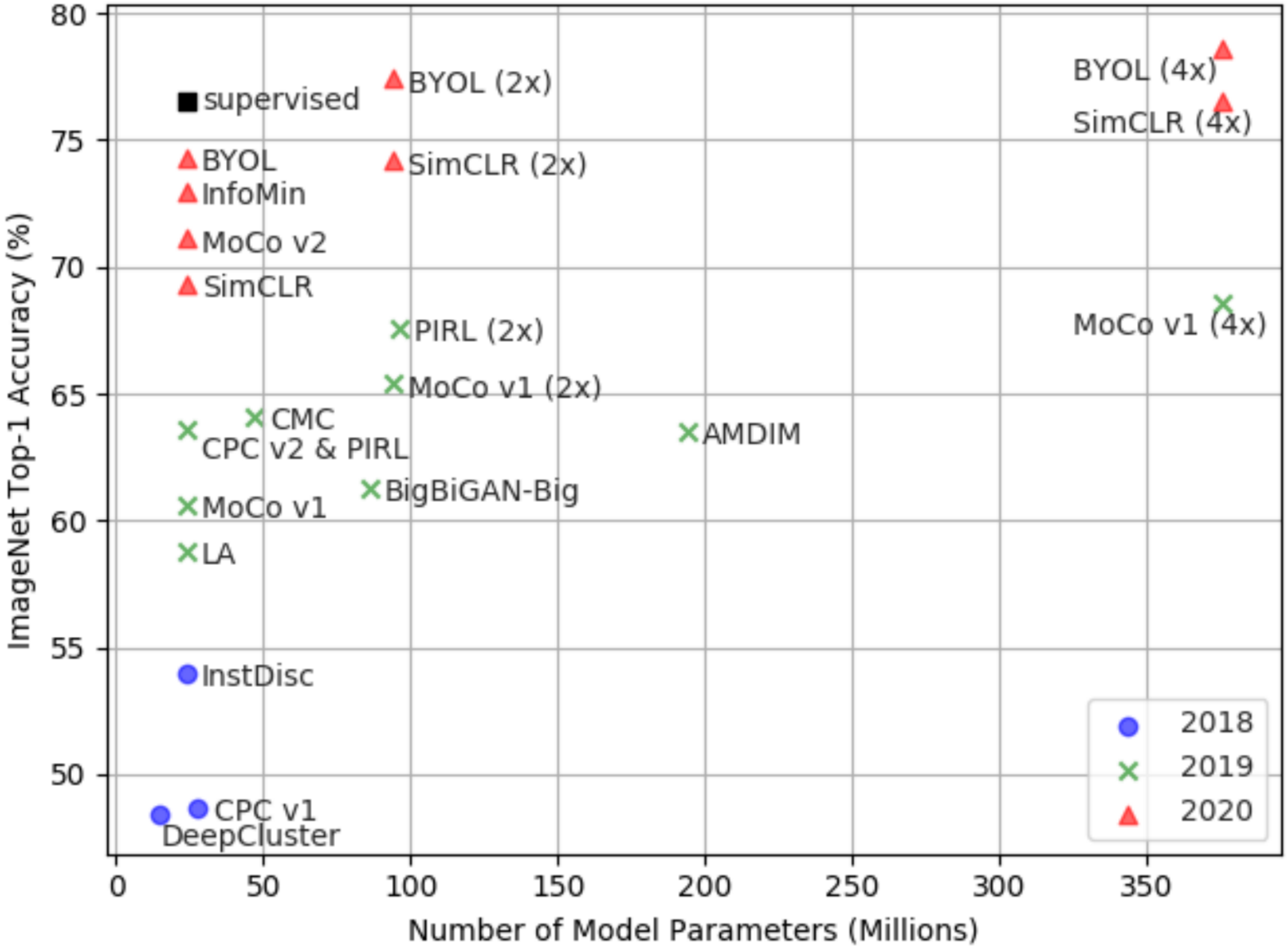
BERTje [33], CamemBERT [125], FlauBERT [95], RobBERT [35]
Multi-Modal
Image
ViLBERT [120], LXMERT [175],
VisualBERT [103], B2T2 [2], VL-BERT [163]
Video
VideoBERT [165], CBT [164]
Speech
SpeechBERT [22]
Domain-Specific
SentiLR [83], BioBERT [98], SciBERT [11], PatentBERT [97]
Model Compression
Model Pruning
CompressingBERT [51]
Quantization
Q-BERT [156], Q8BERT [211]
Parameter Sharing
ALBERT [93]
Distillation
DistilBERT [152], TinyBERT [75], MiniLM [194]
Module Replacing
BERT-of-Theseus [203]

Pre-training in CV——Self-supervised



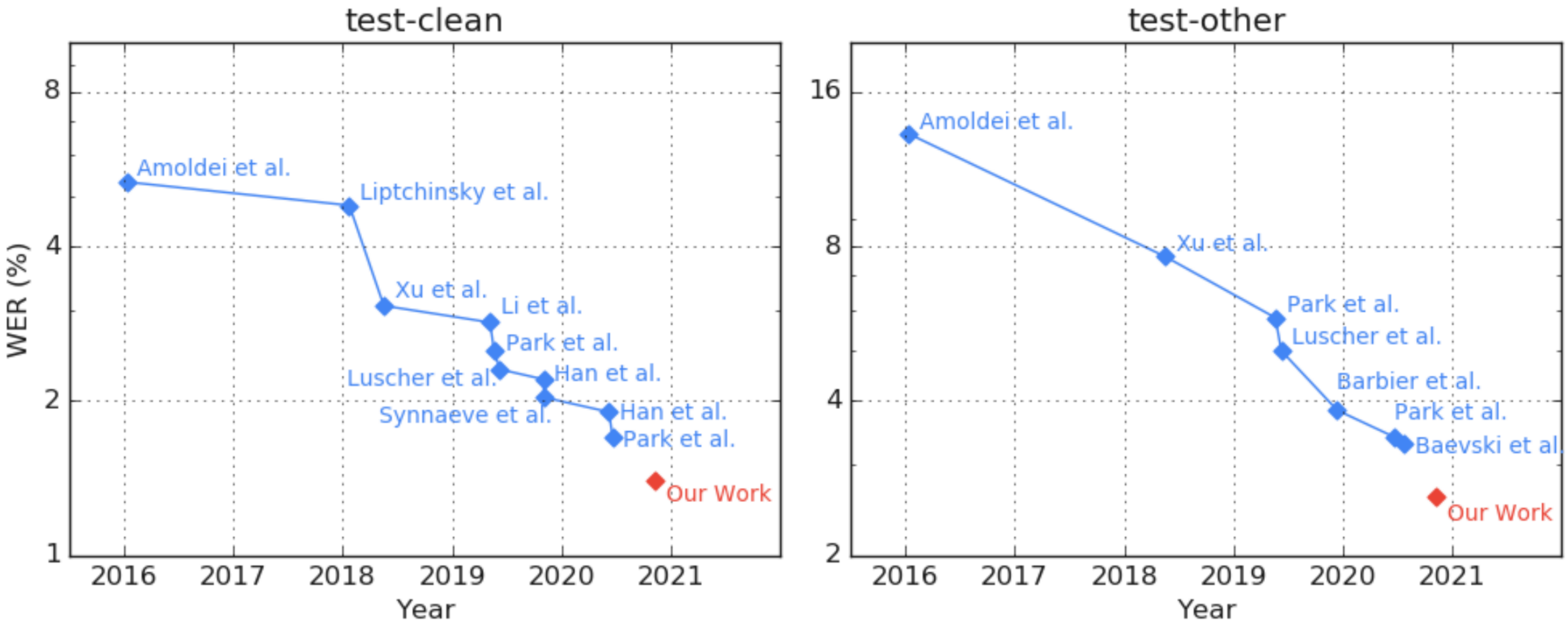
Top 1 accuracy on ImageNet with self-supervised pre-training

Pre-training in CV——Supervised/Semi-supervised

Rank	Model	Top 1 Accuracy	Top 5 Accuracy	Number of params	Extra Training Data	Code	Result	Year
1	**Meta Pseudo Labels** (EfficientNet-L2) Meta Pseudo Labels	90.2%	98.8%	480M	✓			2021
2	**Meta Pseudo Labels** (EfficientNet-B6-Wide) Meta Pseudo Labels	90%	98.7%	390M	✓			2021
3	**NFNet-F4+** High-Performance Large-Scale Image Recognition Without Normalization	89.2%		527M	✓			2021
4	**ALIGN** (EfficientNet-L2) Scaling Up Visual and Vision-Language Representation Learning With Noisy Text Supervision	88.64%	98.67%	480M	✓			2021
5	**EfficientNet-L2-475** (SAM) Sharpness-Aware Minimization for Efficiently Improving Generalization	88.61%		480M	✓			2020
6	**ViT-H/14** An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale	88.55%		632M	✓			2020
7	**FixEfficientNet-L2** Fixing the train-test resolution discrepancy: FixEfficientNet	88.5%	98.7%	480M	✓			2020
8	**NoisyStudent** (EfficientNet-L2) Self-training with Noisy Student improves ImageNet classification	88.4%	98.7%	480M	✓			2020
9	**Mixer-H/14** (JFT-300M pre-train) MLP-Mixer: An all-MLP Architecture for Vision	87.94%			✓			2021
10	**ViT-L/16** An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale	87.76%		307M	✓			2020

Top 1 accuracy on ImageNet with supervised/semi-supervised pre-training

Pre-training in Speech



SOTA WER on LibriSpeech with self-supervised and semi-supervised training

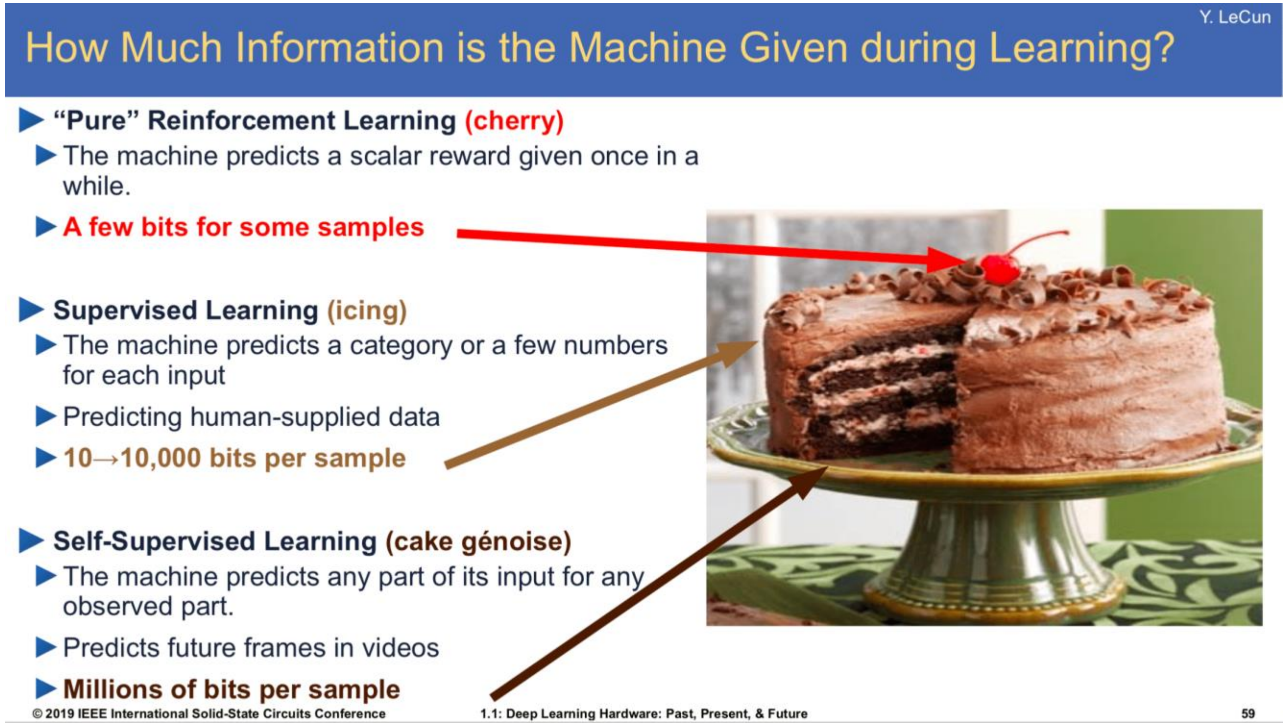
Pre-training in Speech

Rank	Model	Word Error Rate (WER)	Extra Training Data	Code	Result	Year
1	**Conformer + Wav2vec 2.0 + SpecAugment-based Noisy Student Training with Libri-Light** Pushing the Limits of Semi-Supervised Learning for Automatic Speech Recognition	1.4	✓			2020
2	**Conv + Transformer + wav2vec2.0 + pseudo labeling** Self-training and Pre-training are Complementary for Speech Recognition	1.5	✓			2020
3	**ContextNet + SpecAugment-based Noisy Student Training with Libri-Light** Improved Noisy Student Training for Automatic Speech Recognition	1.7	✓			2020
4	**SpeechStew** (1B) SpeechStew: Simply Mix All Available Speech Recognition Data to Train One Large Neural Network	1.7	✕			2021
5	**Multistream CNN with Self-Attentive SRU** ASAPP-ASR: Multistream CNN and Self-Attentive SRU for SOTA Speech Recognition	1.75	✕			2020
6	**wav2vec 2.0 with Libri-Light** wav2vec 2.0: A Framework for Self-Supervised Learning of Speech Representations	1.8	✓			2020
7	**ContextNet** (L) ContextNet: Improving Convolutional Neural Networks for Automatic Speech Recognition with Global Context	1.9	✕			2020
8	**Conformer** (L) Conformer: Convolution-augmented Transformer for Speech Recognition	1.9	✕			2020

SOTA WER on LibriSpeech with self-supervised and semi-supervised training

How to learn in pre-training

- Learning paradigm
  - Supervised learning
  - Unsupervised learning
  - Semi-supervised learning
  - Reinforcement learning
  - Transfer learning
  - Self-supervised learning
- Pre-training
  - In this talk, we focus more on self-supervised learning
  - Context based and contrast based

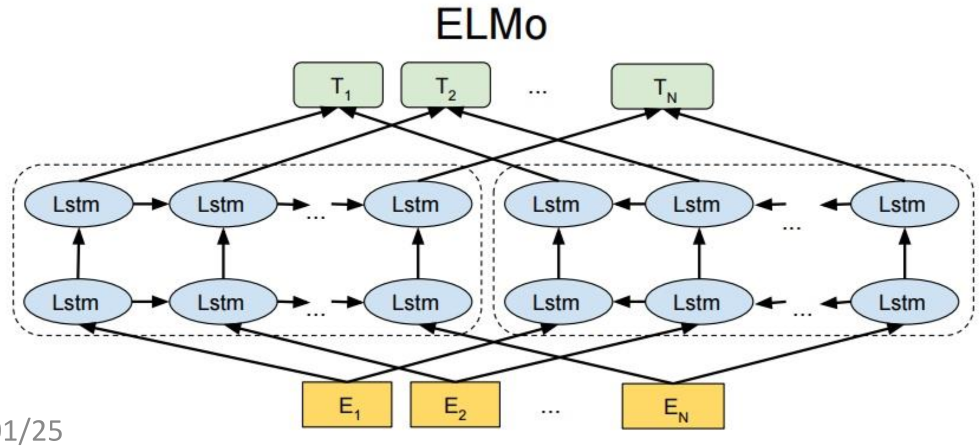


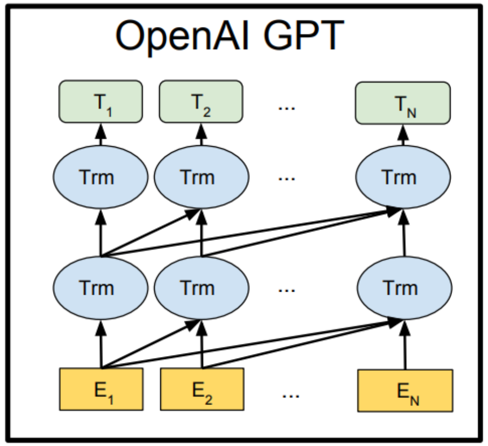
Context based vs Contrast based

- Context based
  - Autoregressive Language Model (LM): ELMo [3], GPT-1/2/3 [4,5,6]
  - Denoising Auto-Encoder (DAE): MLM (BERT[7], RoBERTa[9], ERNIE[21,23], UniLM[14], XLM [15]), Seq2SeqMLM (MASS [11], T5 [17], ProphetNet [43], BART[12])
  - Permuted Language Model (PLM): XLNet [10], MPNet [27]
- Contrast based
  - Context-Instance Contrast
    - Predict Relative Position (PRP): Jigsaw, Rotation Angle [45], Sentence Order Prediction (ALBERT [19], StructBERT [20])
    - Maximize Mutual Information (MI): Deep InfoMax/InforWord [28], AMDIM [29], Contrastive Predictive Coding [30] (wav2vec [41,42]), Replaced Token Detection (word2vec [1], ELECTRA[18])
  - Context-Context Contrast
    - DeepCluster [32], CMC [31], MoCo [34,37], SimCLR [35,38], BYOL [36], Next Sentence Prediction (BERT [7])

Context based: LM

- Language model $\mathcal{L}_{\mathrm{LM}} = -\sum_{t=1}^{T} \log p(x_t|\mathbf{x}_{<t})$
  - Natural, Joint probability estimation
  - Left to right, no bidirectional context information
- ELMo [3], GPT [4], GPT-2 [5], GPT-3 [6]
  - ELMo: NAACL 2018 best paper, GPT-3: NeurIPS 2020 best paper
  - GPT-3 has 175 billion parameters, the largest model before (1.7 Trillion, Switch Transformer [46])





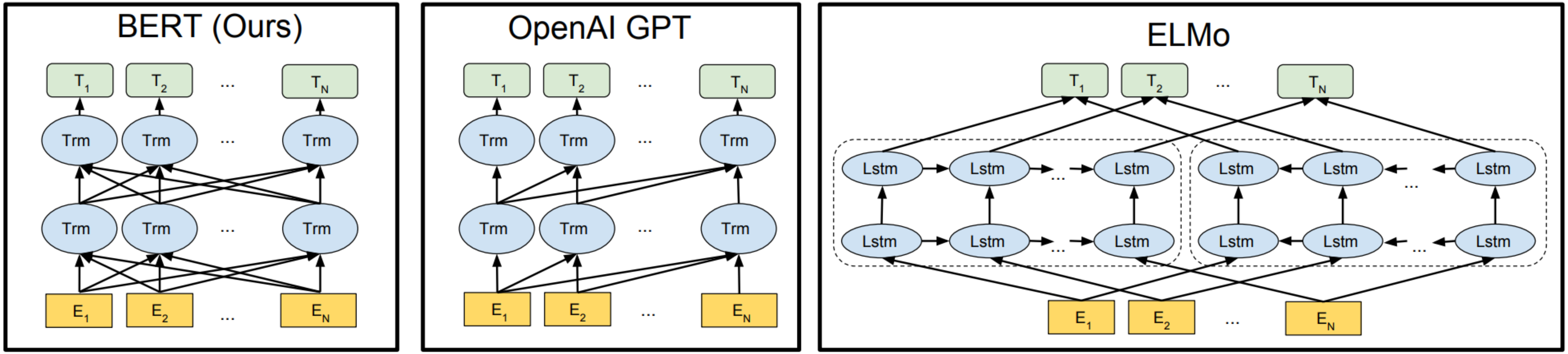
Context based: DAE

- Denoising Auto-Encoder
  - DAE: Noisy Input, reconstruct whole clean input $$\mathcal{L}_{\text{DAE}} = -\sum_{t=1}^{T} \log p(x_t|\hat{\mathbf{x}}, \mathbf{x}_{<t})$$
  - MLM: Noisy Input (with mask tokens), reconstruct mask tokens $$\mathcal{L}_{\text{MLM}} = -\sum_{\hat{x}\in m(\mathbf{x})} \log p\left(\hat{x}|\mathbf{x}_{\backslash m(\mathbf{x})}\right)$$
  - Seq2SeqMLM: Noisy Input (with mask tokens), reconstruct mask tokens, with encoder-decoder framework $$\mathcal{L}_{\text{S2SMLM}} = -\sum_{t=i}^{j} \log p\left(x_t|\mathbf{x}_{\backslash \mathbf{x}_{i:j}}, \mathbf{x}_{i:t-1}\right)$$

- BERT [7], MASS [11], RoBERTa [9], XLM [15], ERNIE [21,23], UniLM [14], ProphetNet [43], T5 [17], BART [12]

Context based: MLM——BERT

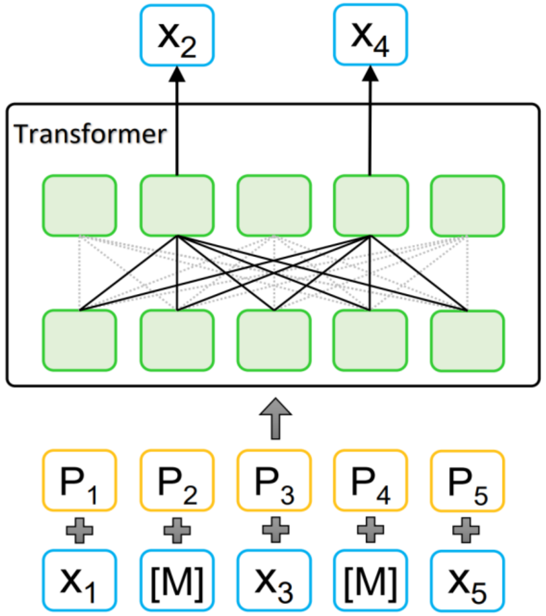
- BERT [7]: Bidirectional transformer, vs GPT [4,5,6], ELMo [3]

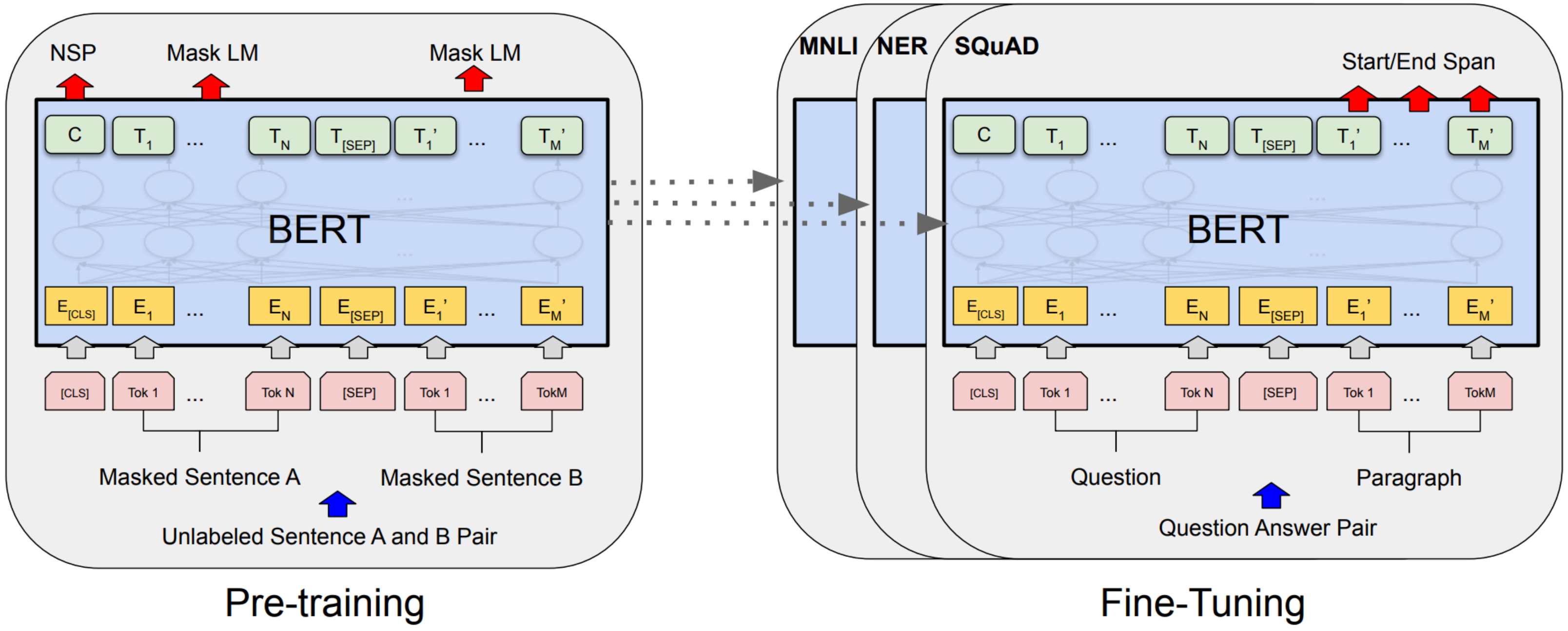


[7] Devlin, Jacob, et al. "Bert: Pre-training of deep bidirectional transformers for language understanding." *NAACL 2019*

Context based: MLM——BERT

- BERT [7]: Bidirectional transformer

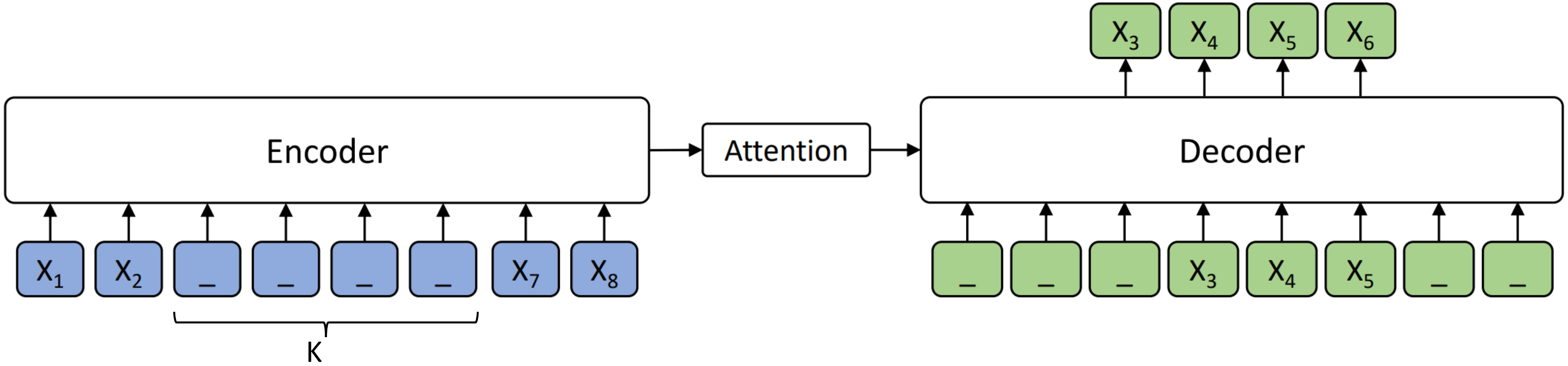




[7] Devlin, Jacob, et al. "Bert: Pre-training of deep bidirectional transformers for language understanding." *NAACL 2019*

Context based: Seq2SeqMLM——MASS

- MASS: MAsked Sequence to Sequence pre-training [11]
  - MASS is carefully designed to jointly pre-train the encoder and decoder



- Mask k consecutive tokens (a sentence segment)
  - **Force the decoder to attend on the source representations, i.e., encoder-decoder attention.**
  - Force the encoder to extract meaningful information from the sentence.
  - Develop the decoder with the ability of language modeling.

[11] Kaitao Song, Xu Tan, Tao Qin, Jianfeng Lu, Tie-Yan Liu. MASS: Masked sequence to sequence pre-training for language generation. ICML 2019

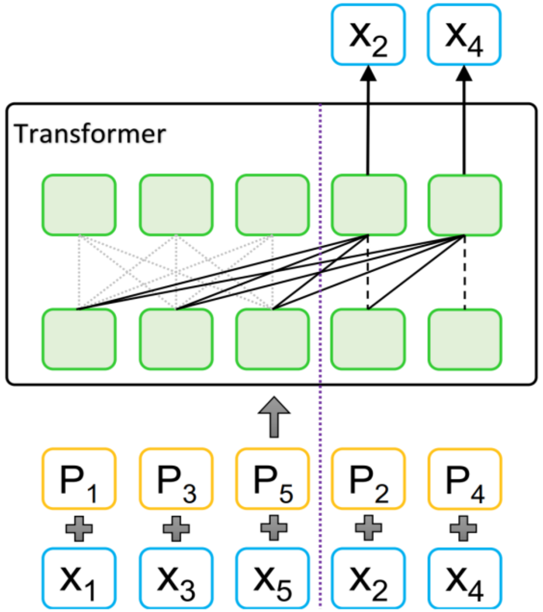
Context based: PLM

- Permuted Language Model $\mathcal{L}_{\text{PLM}} = -\sum_{t=1}^{T} \log p(z_t | \mathbf{z}_{<t})$
    - A generalized autoregressive language model, random permute the sentence order, better use language model for pre-training
    - Combine the advantages of LM and MLM
        - LM: only left context, MLM: bidirectional context
        - LM: conditional dependent, MLM: conditional independent
- XLNet [10], MPNet [27]

[10] Zhilin Yang, Zihang Dai, Yiming Yang, Jaime Carbonell, Russ R Salakhutdinov, and Quoc V Le. XLNet: Generalized autoregressive pretraining for language understanding. In NeurIPS, pages 5754–5764, 2019.
[27] Kaitao Song, Xu Tan, Tao Qin, Jianfeng Lu, Tie-Yan Liu. MPNet: Masked and permuted pre-training for language understanding. NeurIPS 2020.

Context based: PLM——XLNet

- Key designs in XLNet
  - Autoregressive model, use permuted language model (PLM) to introduce bidirectional context
  - Two-stream self-attention to decide the position of next predicted token
  - Use Transformer-XL to incorporate long context

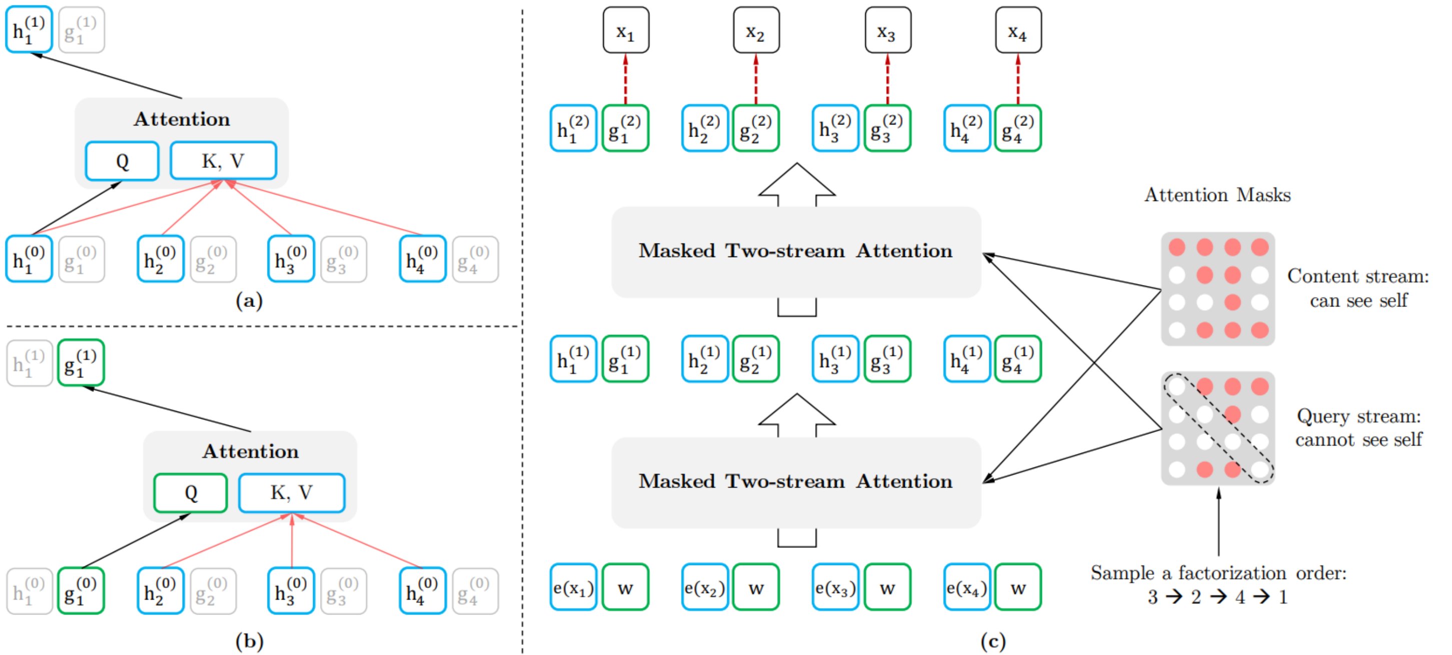


$$\log P(x;\theta) = \mathbb{E}_{z\in\mathcal{Z}_n} \sum_{t=c+1}^{n} \log P(x_{z_t} | x_{z_{<t}}; \theta)$$

Context based: PLM——XLNet

- Two-stream self-attention
  - Content stream: build content hidden, same as GPT/BERT in Transformer
  - Query stream: token prediction, use position as input to decide which token to predict

$$g_{z_t}^{(m)} \leftarrow \text{Attention}(\mathrm{Q} = g_{z_t}^{(m-1)}, \mathrm{KV} = \mathbf{h}_{\mathbf{z}_{<t}}^{(m-1)}; \theta), \quad (\text{query stream: use } z_t \text{ but cannot see } x_{z_t})$$
$$h_{z_t}^{(m)} \leftarrow \text{Attention}(\mathrm{Q} = h_{z_t}^{(m-1)}, \mathrm{KV} = \mathbf{h}_{\mathbf{z}_{\leq t}}^{(m-1)}; \theta), \quad (\text{content stream: use both } z_t \text{ and } x_{z_t}).$$



Context based: PLM——XLNet

- Transformer-XL
  - Recurrence mechanism: cache and reuse the representation of previous segment

$$h_{z_t}^{(m)} \leftarrow \text{Attention}(\mathrm{Q} = h_{z_t}^{(m-1)}, \mathrm{KV} = \left[\tilde{\mathbf{h}}^{(m-1)}, \mathbf{h}_{\mathbf{z}_{\leq t}}^{(m-1)}\right]; \theta)$$

  - Relative position embedding
    - Do not care the absolute position, but only relative position

$$\begin{aligned}\mathbf{A}_{i,j}^{\text{abs}} &= \underbrace{\mathbf{E}_{x_i}^\top \mathbf{W}_q^\top \mathbf{W}_k \mathbf{E}_{x_j}}_{(a)} + \underbrace{\mathbf{E}_{x_i}^\top \mathbf{W}_q^\top \mathbf{W}_k \mathbf{U}_j}_{(b)} \\ &+ \underbrace{\mathbf{U}_i^\top \mathbf{W}_q^\top \mathbf{W}_k \mathbf{E}_{x_j}}_{(c)} + \underbrace{\mathbf{U}_i^\top \mathbf{W}_q^\top \mathbf{W}_k \mathbf{U}_j}_{(d)}.\end{aligned}$$

$$\begin{aligned}\mathbf{A}_{i,j}^{\text{rel}} &= \underbrace{\mathbf{E}_{x_i}^\top \mathbf{W}_q^\top \mathbf{W}_{k,E} \mathbf{E}_{x_j}}_{(a)} + \underbrace{\mathbf{E}_{x_i}^\top \mathbf{W}_q^\top \mathbf{W}_{k,R} \mathbf{R}_{i-j}}_{(b)} \\ &+ \underbrace{u^\top \mathbf{W}_{k,E} \mathbf{E}_{x_j}}_{(c)} + \underbrace{v^\top \mathbf{W}_{k,R} \mathbf{R}_{i-j}}_{(d)}.\end{aligned}$$

Context based: PLM——XLNet

- The advantage of XLNet (the task is sentence classification)
  - Bidirectional context, vs GPT

Objective	Modeling
LM (GPT)	log P(is | the task)
PLM (XLNet)	log P(is| the task) + log P(is | sentence classification)

  - Dependency between predicted tokens, vs BERT

Objective	Modeling
MLM (BERT)	log P(sentence| the task is) + log P(classification| the task is)
PLM (XLNet)	log P(sentence| the task is) + log P(classification| the task is sentence)

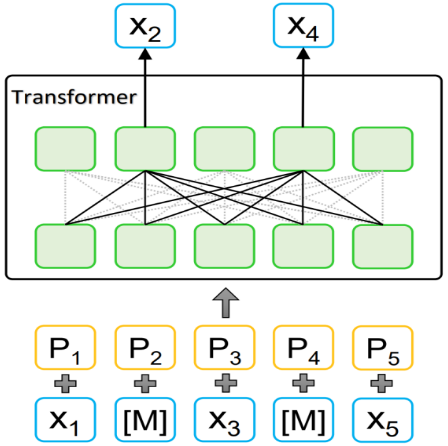
Context based: MLM+PLM——MPNet

- The pros and cons of BERT and XLNet
  - “the task is sentence classification”, predict token “sentence” and “classification”

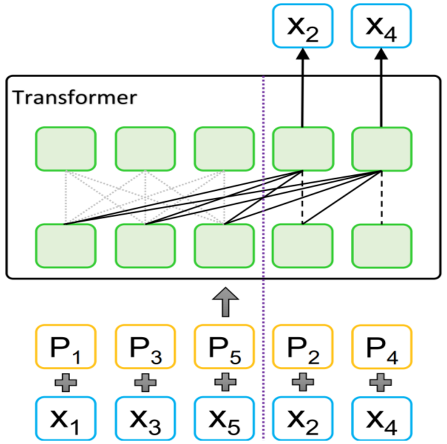
Objective	Modeling
MLM (BERT)	log P(sentence | the task is [M] [M]) + log P(classification | the task is [M] [M])
PLM (XLNet)	log P(sentence | the task is) + log P(classification | the task is sentence)

full position information

dependency



MLM (BERT)



PLM (XLNet)

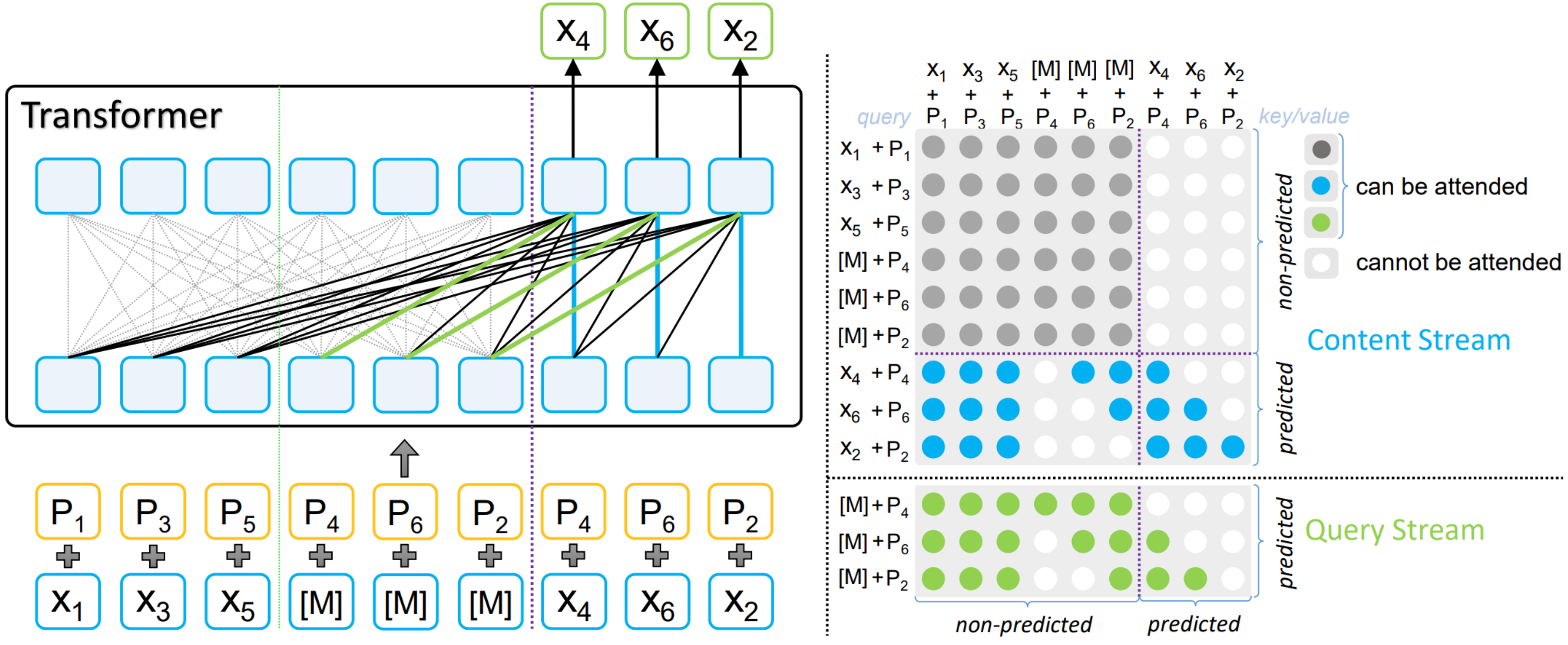
- Two aspects
  - Output dependency: dependency among the masked/predicted tokens
  - Input consistency: position information between pre-training and fine-tuning

	Output Dependency	Input Consistency
MLM (BERT)	×	√
PLM (XLNet)	√	×

MPNet: inherit their advantages but avoid their limitations

Context based: MLM+PLM——MPNet

- **Autoregressive prediction** (avoid the limitation in BERT)
  - Each predicted token condition on previous predicted tokens to ensure **output dependency**
- **Position compensation** (avoid the limitation in XLNet)
  - Each predicted token can see full position information to ensure **input consistency**



(a) (b)

Context based: MLM+PLM——MPNet

- The advantages of MPNet

Objective	Modeling
MLM (BERT)	log P(sentence | the task is [M] [M]) + log P(classification | the task is [M] [M])
PLM (XLNet)	log P(sentence | the task is) + log P(classification | the task is sentence)
MPNet	log P(sentence | the task is [M] [M]) + log P(classification | the task is sentence [M])

- Position compensation, input consistency, **vs. PLM (XLNet)**
  - MPNet knows 2 tokens to predict, instead of 3 tokens like “sentence pair classification”
- Autoregressive prediction, output dependency, **vs. MLM (BERT)**
  - MPNet can better predict “classification” given previous token “sentence”, instead of predicting “answering” as if to predict “question answering”

Context based: MLM+PLM——MPNet

- The advantages of MPNet

Objective	Modeling
MLM (BERT)	log P(sentence | the task is [M] [M]) + log P(classification | the task is [M] [M])
PLM (XLNet)	log P(sentence | the task is) + log P(classification | the task is sentence)
MPNet	log P(sentence | the task is [M] [M]) + log P(classification | the task is sentence [M])

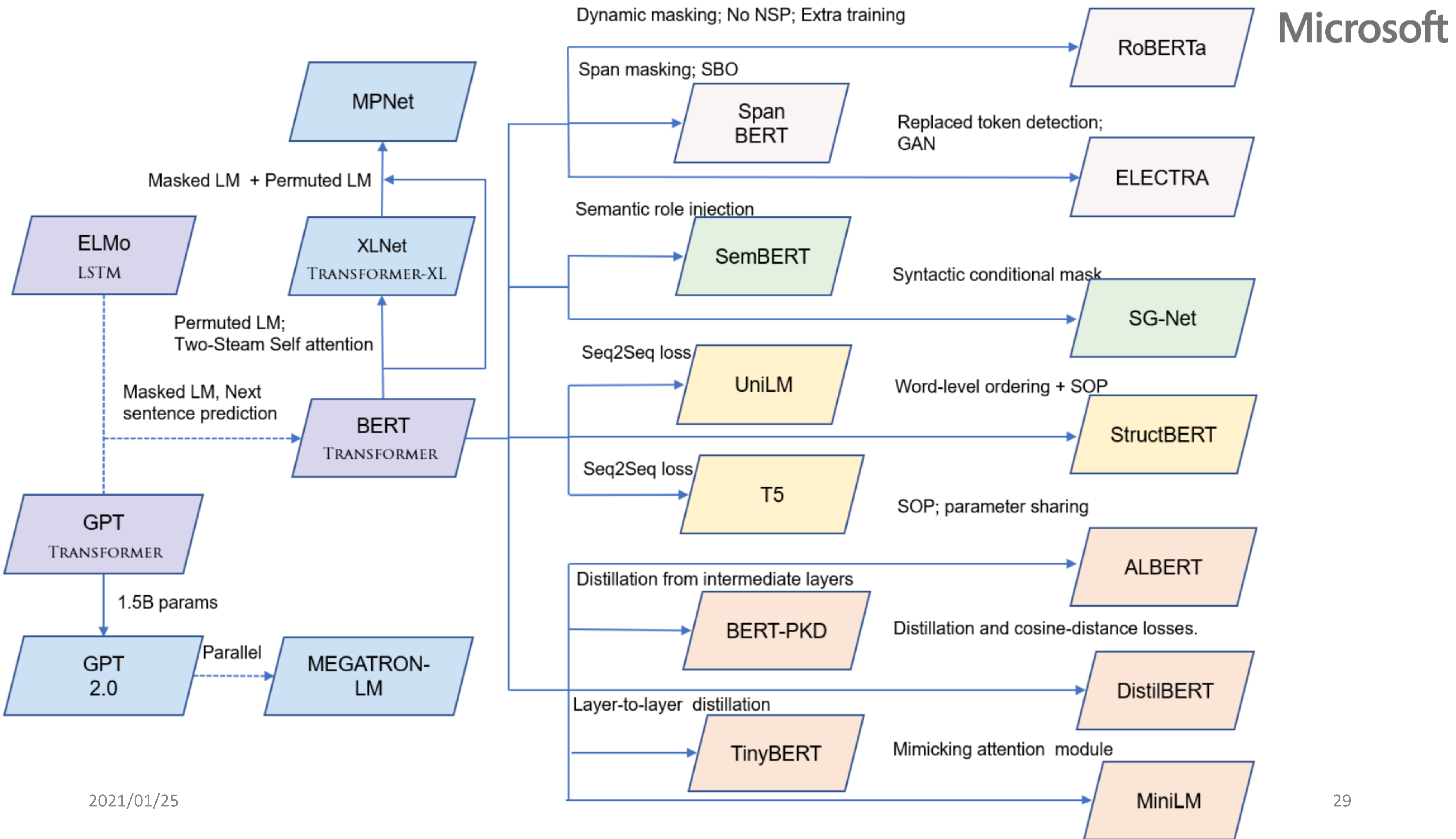
- How much conditional information is used on average to predict a masked token? (assume all objectives mask and predict 15% tokens)

Objective	Formulation	#Tokens	#Positions
MLM (BERT)	$\sum_{t=c+1}^{n} \log P(x_{z_t} \| x_{z_{<=c}}, M_{z_{>c}}; \theta)$	85%	100%
PLM (XLNet)	$\sum_{t=c+1}^{n} \log P(x_{z_t} \| x_{z_{<t}}; \theta)$	92.5%	92.5%
MPNet	$\sum_{t=c+1}^{n} \log P(x_{z_t} \| x_{z_{<t}}, M_{z_{>c}}; \theta)$	92.5%	100%

Inherit their advantages

Avoid their limitations

MPNet uses the most information to predict tokens


Microsoft
MPNet
Masked LM + Permuted LM
ELMo
LSTM
XLNet
TRANSFORMER-XL
Permuted LM;
Two-Steam Self attention
Masked LM, Next
sentence prediction
BERT
TRANSFORMER
GPT
TRANSFORMER
1.5B params
GPT
2.0
Parallel
MEGATRON-
LM
Dynamic masking; No NSP; Extra training
RoBERTa
Span masking; SBO
Span
BERT
Replaced token detection;
GAN
ELECTRA
Semantic role injection
SemBERT
Syntactic conditional mask
SG-Net
Seq2Seq loss
UniLM
Word-level ordering + SOP
StructBERT
Seq2Seq loss
T5
SOP; parameter sharing
ALBERT
Distillation from intermediate layers
BERT-PKD
Distillation and cosine-distance losses.
DistilBERT
Layer-to-layer distillation
TinyBERT
Mimicking attention module
MiniLM

Context based vs Contrast based

- Context based
  - Autoregressive Language Model (LM): ELMo [3], GPT-1/2/3 [4,5,6]
  - Denoising Auto-Encoder (DAE): MLM (BERT[7], RoBERTa[9], ERNIE[21,23], UniLM[14], XLM [15]), Seq2SeqMLM (MASS [11], T5 [17], ProphetNet [43], BART[12])
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    - Maximize Mutual Information (MI): Deep InfoMax/InforWord [28], AMDIM [29], Contrastive Predictive Coding [30] (wav2vec [41,42]), Replaced Token Detection (word2vec [1], ELECTRA[18])
  - Context-Context Contrast
    - DeepCluster [32], CMC [31], MoCo [34,37], SimCLR [35,38], BYOL [36], Next Sentence Prediction (BERT [7])

Contrast based

- Basic idea: learn from contrast
  - Tell what is, and tell what is not

$$\mathcal{L}_N = -\mathbb{E}_{x,y+,y-}\left[\log \frac{\exp(s\left(x, y^{+}\right))}{\exp(s(x, y^{+})) + \sum_{j=1}^{N-1} \exp\left(s(x, y_j^{-})\right)}\right]$$

- Different contrast granularities
  - Context-Instance Contrast
  - Context-Context Contrast

Contrast based: Context-Instance Contrast

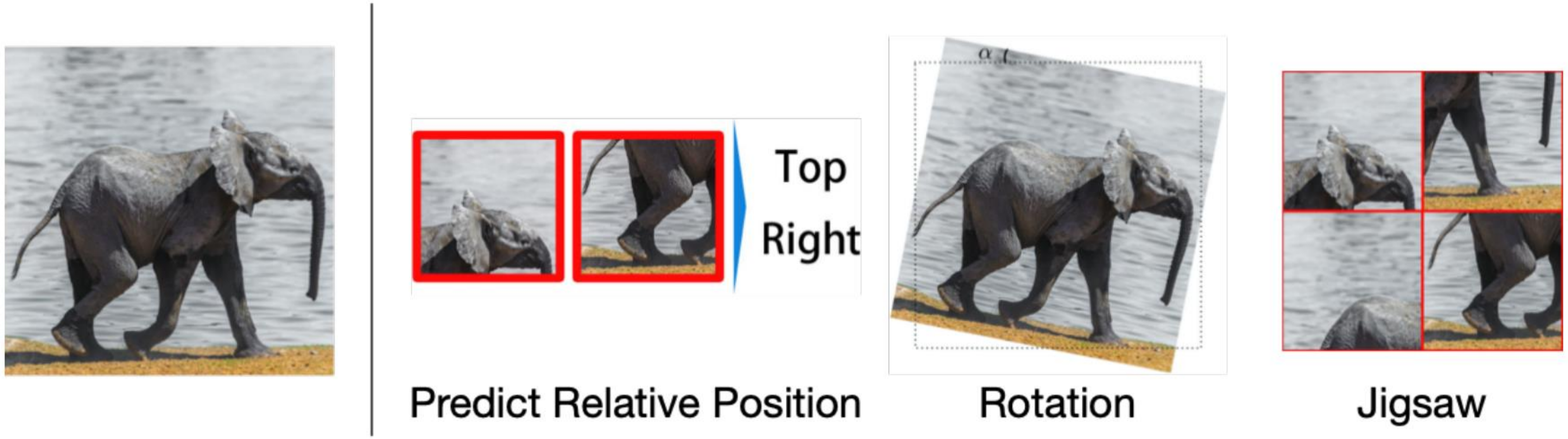
- Context-Instance Contrast: Global-local contrast: the local feature of a sample and its global context representation
  - Patches to their image, sentences to their paragraph, words to their sentence, and nodes to their neighborhoods.

$$\mathcal{L}_N = -\mathbb{E}_{x,y+,y-}\left[\log \frac{\exp(s\left(x, y^{+}\right))}{\exp(s(x, y^{+})) + \sum_{j=1}^{N-1} \exp\left(s(x, y_j^{-})\right)}\right]$$

  - Predict Relative Position (PRP): Jigsaw, Rotation Angle [45], Sentence Order Prediction (ALBERT [19], StructBERT [20])
  - Maximize Mutual Information (MI): Deep InfoMax/InforWord [28], AMDIM [29], Contrastive Predictive Coding [30] (wav2vec [41,42]), Replaced Token Detection (word2vec [1], ELECTRA [18])

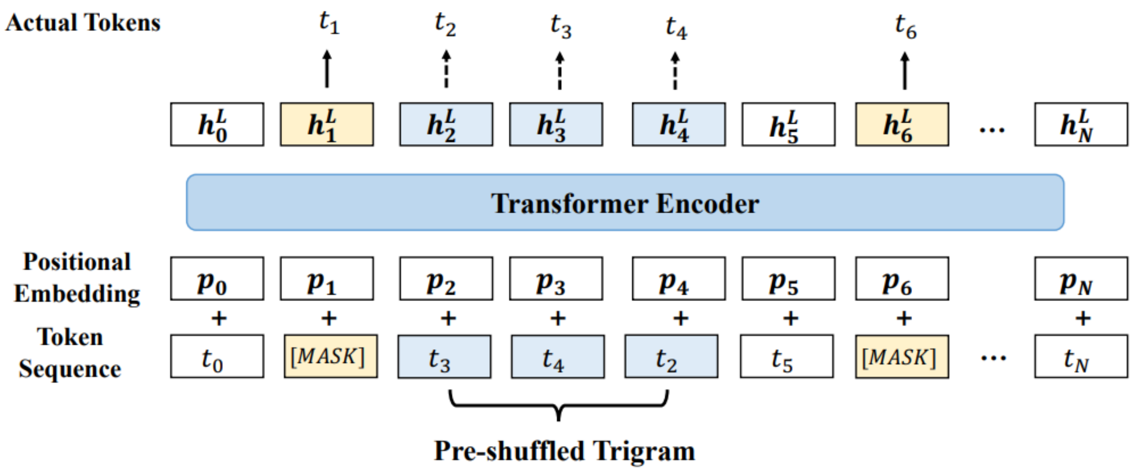
Contrast based: Context-Instance Contrast

- Predict Relative Position (PRP)
  - Jigsaw, rotation angle, relative position [45]

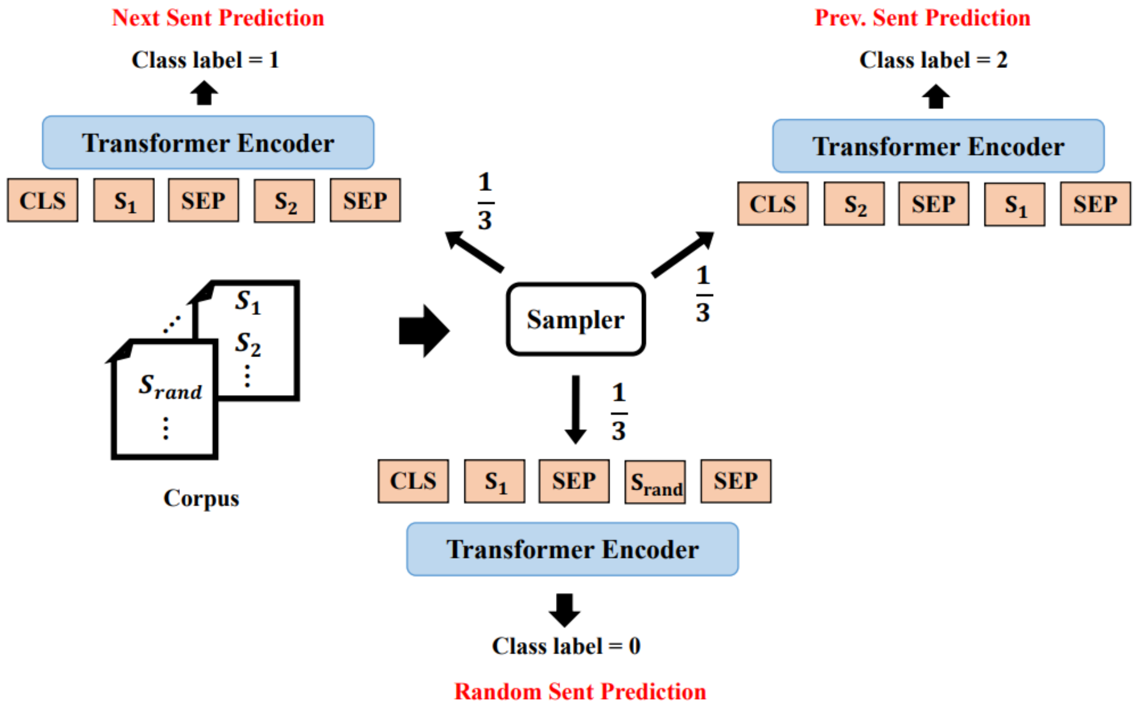


Contrast based: Context-Instance Contrast

- Predict Relative Position (PRP)
  - Next Sentence Prediction (BERT [7])
  - Sentence Order Prediction (ALBERT[19], StructBERT [20])



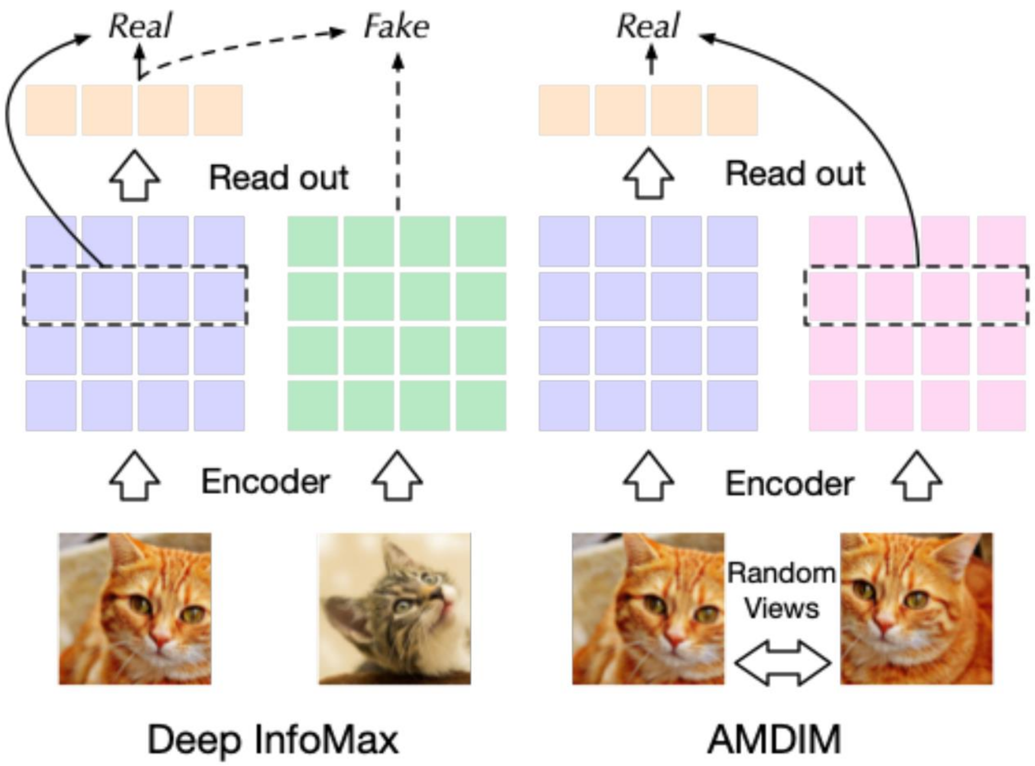
(a) Word Structural Objective



(b) Sentence Structural Objective

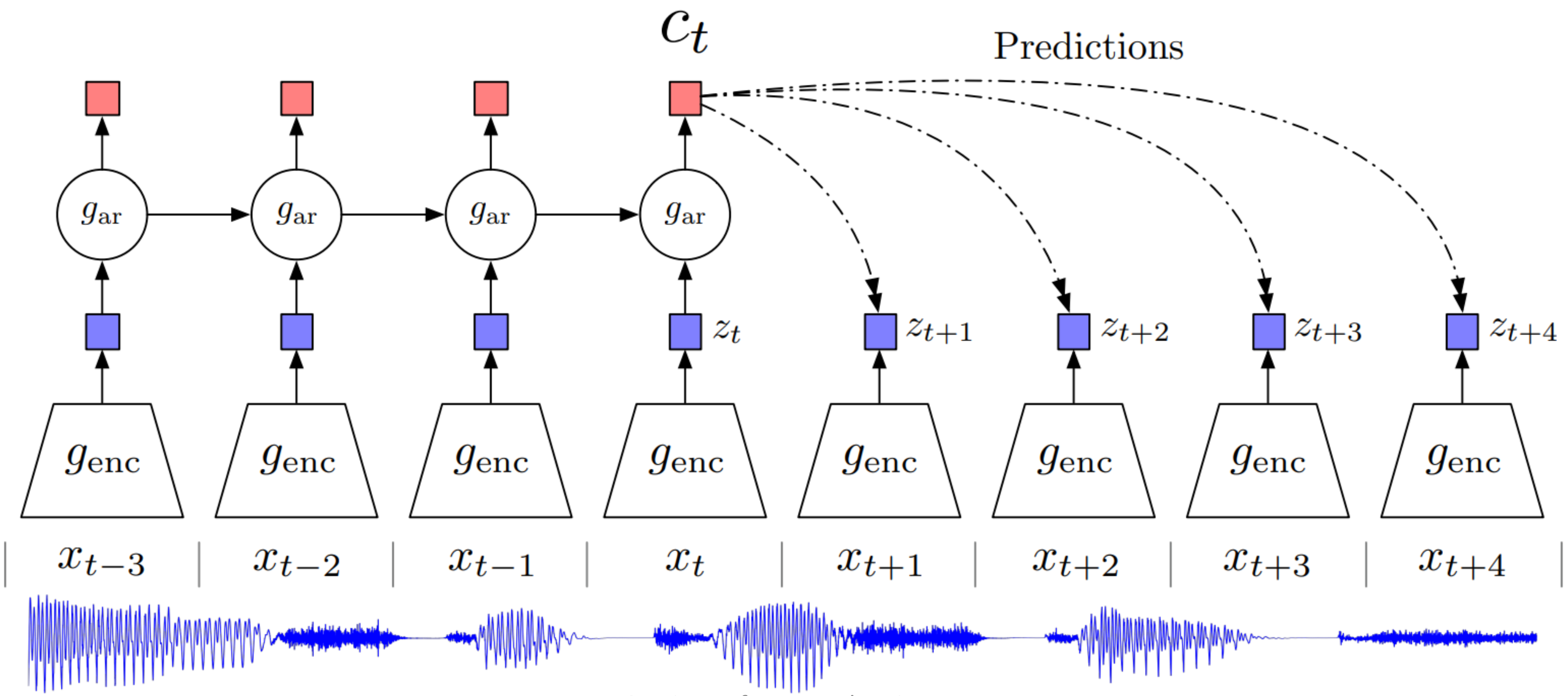
Contrast based: Context-Instance Contrast

- Maximize Mutual Information (MI)
  - Deep InfoMax/InfoWord [28], AMDIM [29]



Contrast based: Context-Instance Contrast

- Maximize Mutual Information (MI)
  - Contrastive Predictive Coding [30]

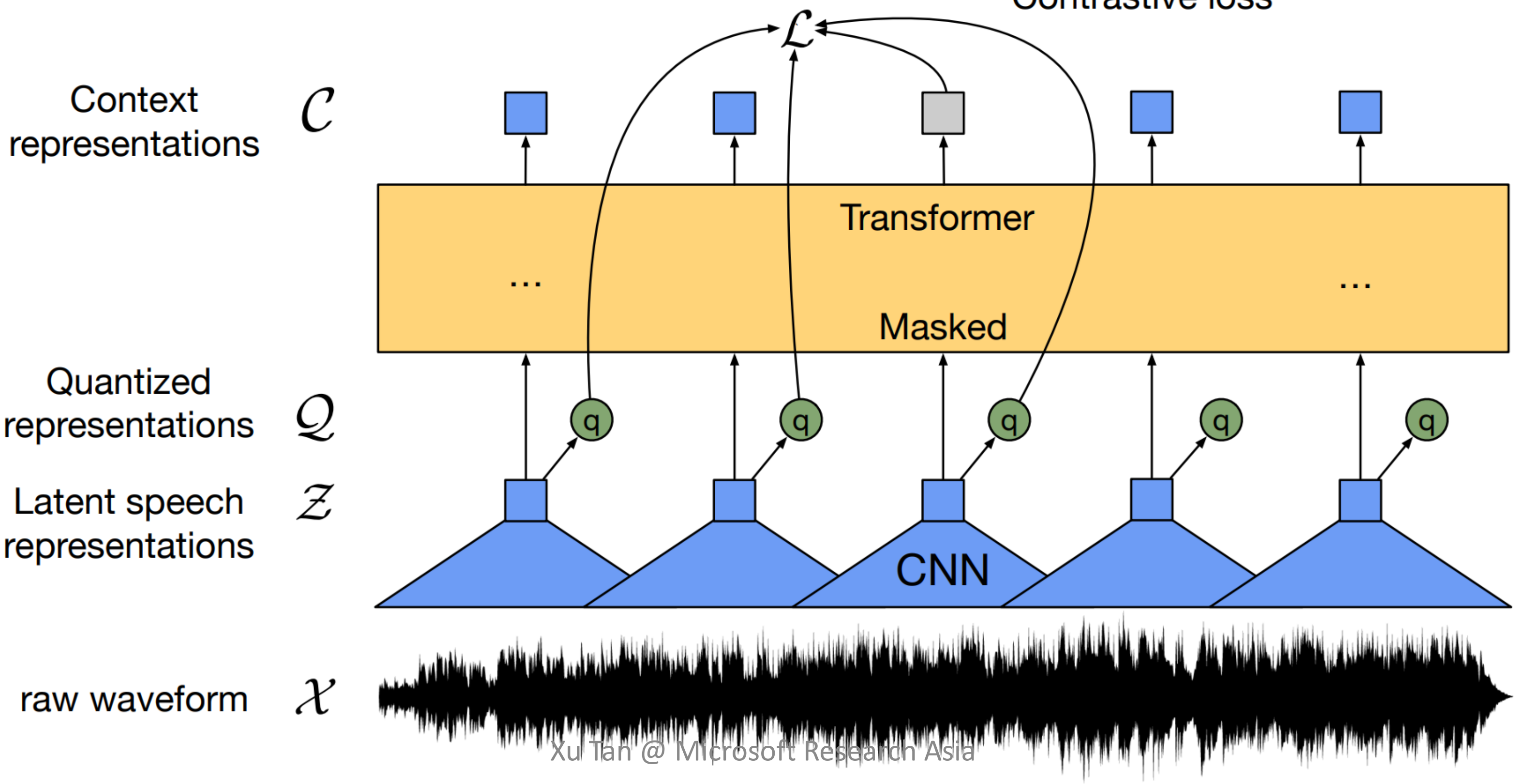


Contrast based: Context-Instance Contrast

- Maximize Mutual Information (MI)
  - Wav2vec /Wav2vec 2.0 [41,42]

$$\mathcal{L}_m = -\log \frac{\exp(sim(\mathbf{c}_t, \mathbf{q}_t)/\kappa)}{\sum_{\tilde{\mathbf{q}} \sim \mathbf{Q}_t} \exp(sim(\mathbf{c}_t, \tilde{\mathbf{q}})/\kappa)}$$

Contrastive loss

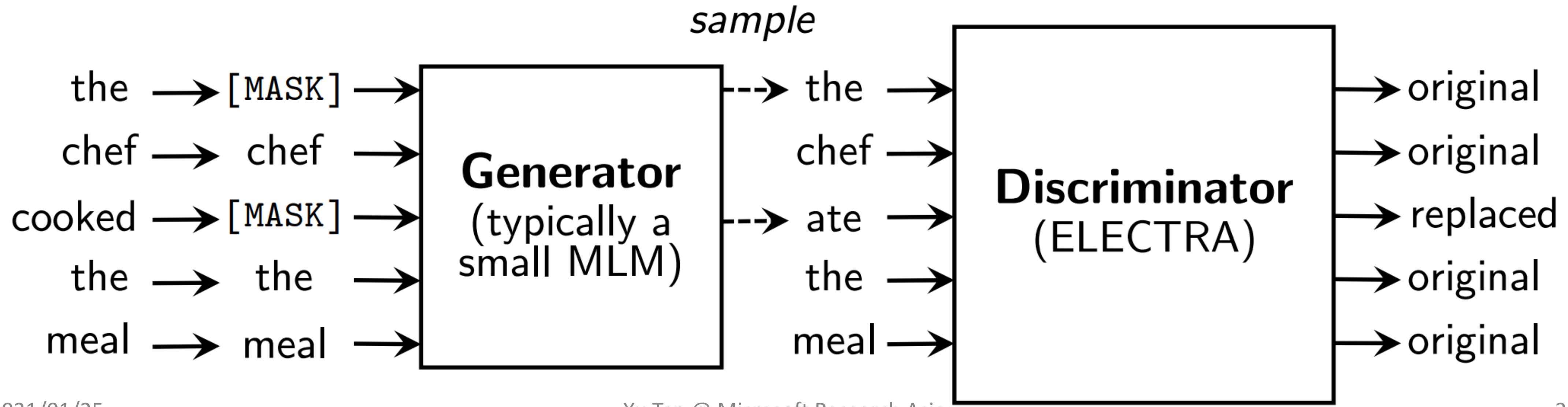


Contrast based: Context-Instance Contrast

- Maximize Mutual Information (MI)
  - Replaced Token Detection (word2vec [1], ELECTRA [18])

$$\mathcal{L}_{\text{RTD}} = -\sum_{t=1}^{T} \log p(y_t|\hat{\mathbf{x}})$$

$$\mathcal{L}_{\text{Disc}}(\boldsymbol{x}, \theta_D) = \mathbb{E}\left(\sum_{t=1}^{n} -\mathbb{1}(x_t^{\text{corrupt}} = x_t) \log D(\boldsymbol{x}^{\text{corrupt}}, t) - \mathbb{1}(x_t^{\text{corrupt}} \neq x_t) \log(1 - D(\boldsymbol{x}^{\text{corrupt}}, t))\right)$$

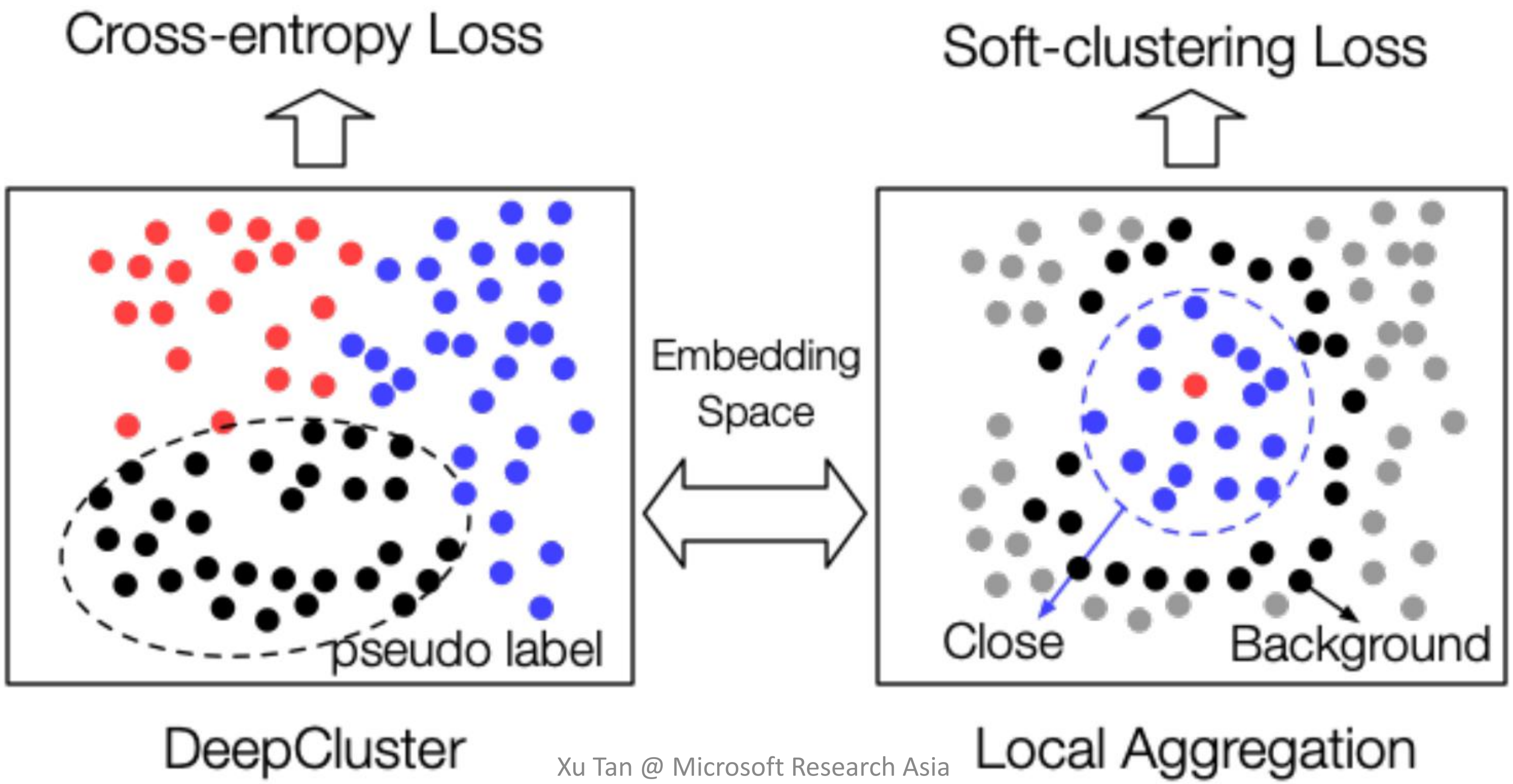


Contrast based: Context-Context Contrast

- Context-Context Contrast: the relationships between the global representations of different samples
  - Cluster-based Discrimination: DeepCluster [32]
  - Instance Discrimination: CMC [31], MoCo [34,37], SimCLR [35,38], BYOL [36]

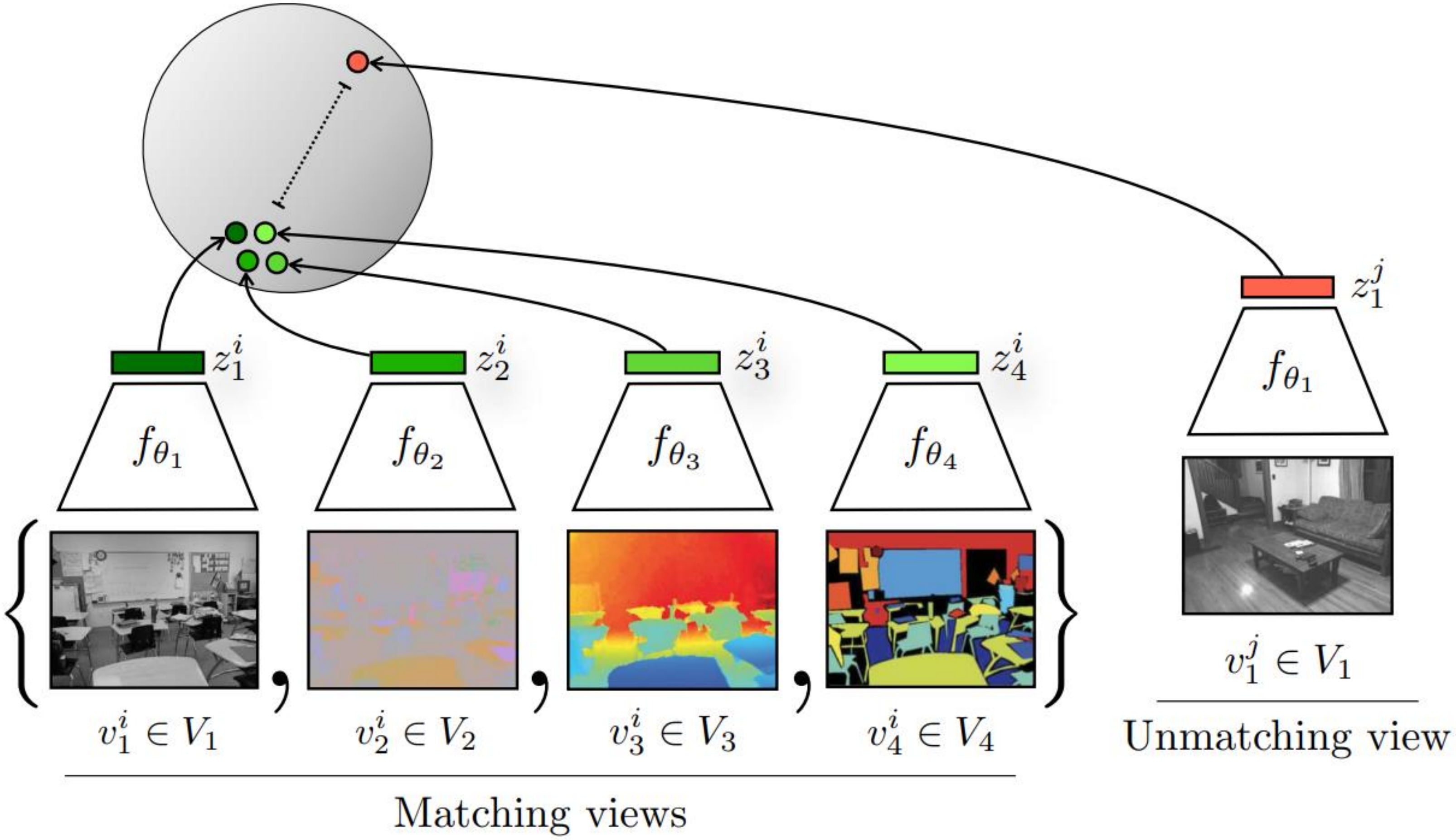
Contrast based: Context-Context Contrast

- Cluster-based Discrimination: DeepCluster [32], Local Aggregation [33]



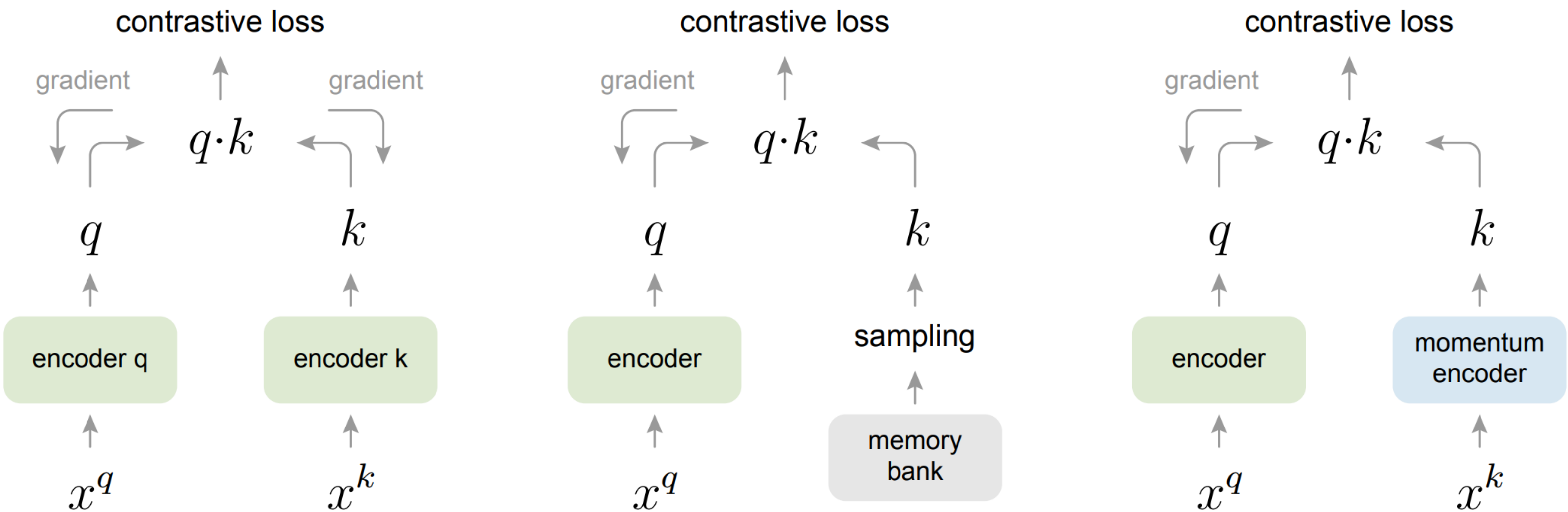
Contrast based: Context-Context Contrast

- Instance Discrimination: Contrastive Multiview Coding (CMC) [31]



Contrast based: Context-Context Contrast

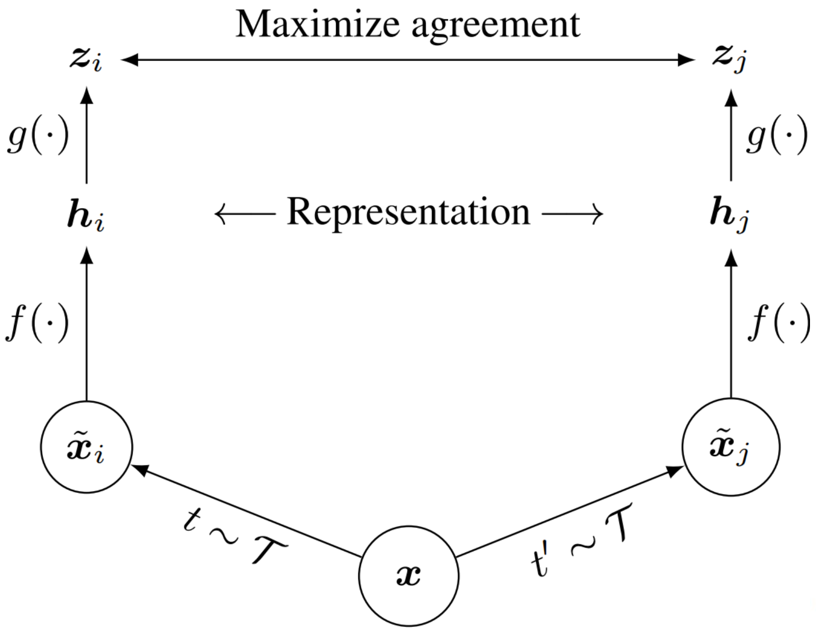
- Instance Discrimination: Momentum Contrast for Unsupervised Visual Representation Learning (MoCo) [34,37]

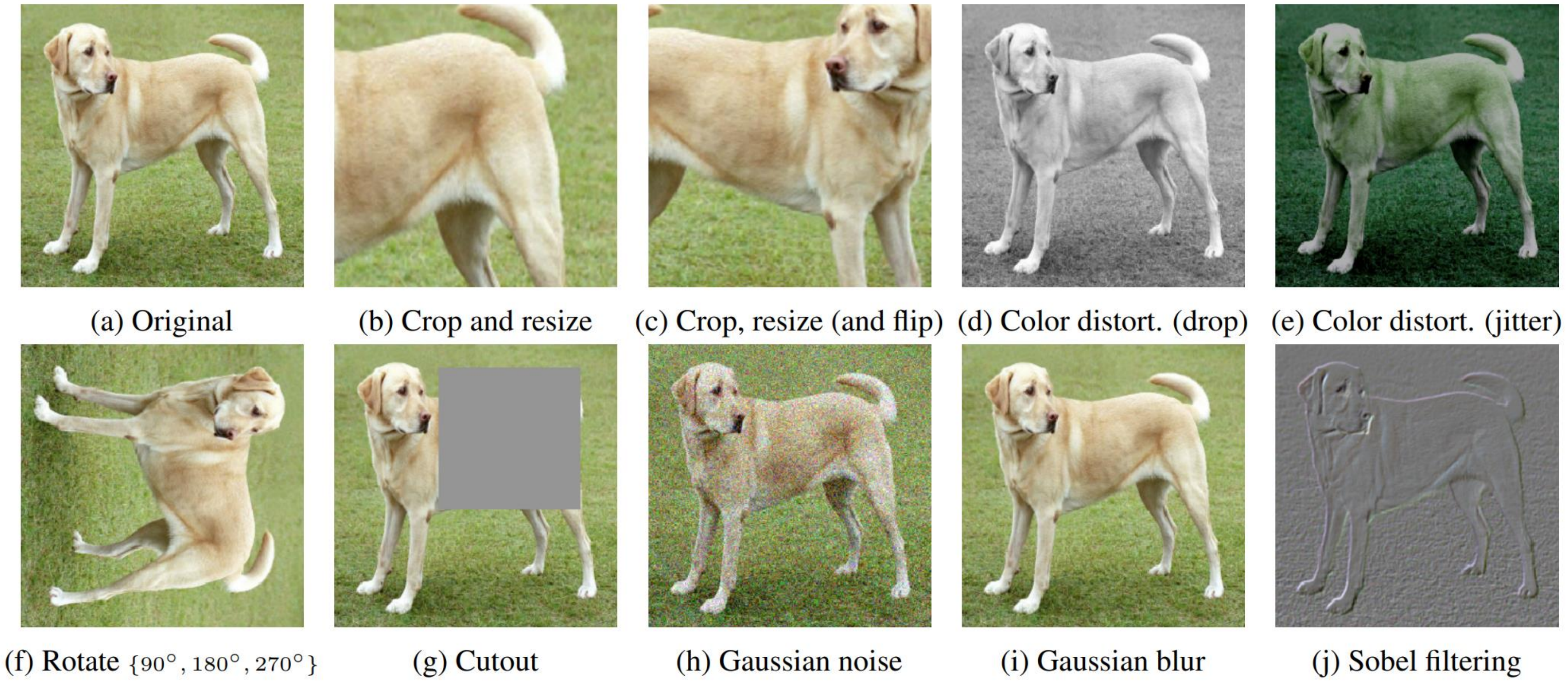


(a) end-to-end (b) memory bank (c) MoCo

Contrast based: Context-Context Contrast

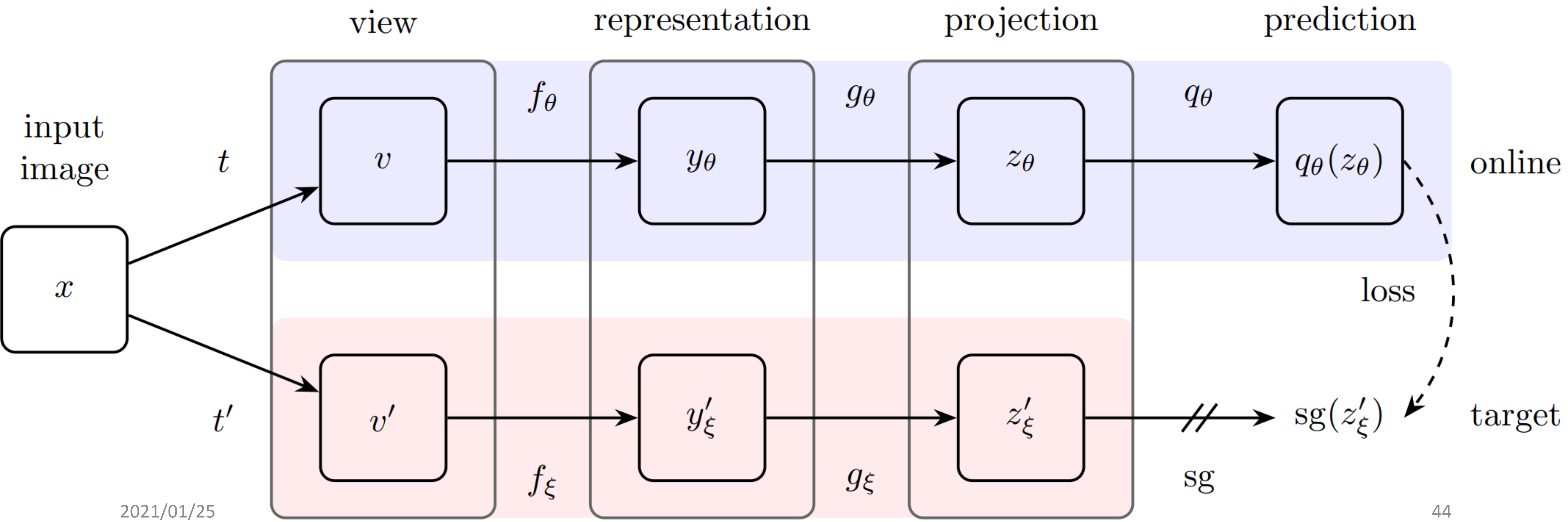
- Instance Discrimination: A Simple Framework for Contrastive Learning of Visual Representations (SimCLR) [35,38]





Contrast based: Context-Context Contrast

- Instance Discrimination: Bootstrap Your Own Latent A New Approach to Self-Supervised Learning (BYOL) [36]



Context based vs Contrast based

- Context based
  - Autoregressive Language Model (LM): ELMo [3], GPT-1/2/3 [4,5,6]
  - Denoising Auto-Encoder (DAE): MLM (BERT[7], RoBERTa[9], ERNIE[21,23], UniLM[14], XLM [15]), Seq2SeqMLM (MASS [11], T5 [17], ProphetNet [43], BART[12])
  - Permuted Language Model (PLM): XLNet [10], MPNet [27]
- Contrast based
  - Context-Instance Contrast
    - Predict Relative Position (PRP): Jigsaw, Rotation Angle [45], Sentence Order Prediction (ALBERT [19], StructBERT [20])
    - Maximize Mutual Information (MI): Deep InfoMax/InforWord [28], AMDIM [29], Contrastive Predictive Coding [30] (wav2vec [41,42]), Replaced Token Detection (word2vec [1], ELECTRA[18])
  - Context-Context Contrast
    - DeepCluster [32], CMC [31], MoCo [34,37], SimCLR [35,38], BYOL [36], Next Sentence Prediction (BERT [7])

How to use pre-training for downstream tasks?

- Choose pre-training task, model structure, data in pre-training
- In fine-tuning
  - Feature incorporation or fine-tunning
  - What to fine-tune? Embedding, partial layers, whole model
  - Different fine-tuning stages, layer-wise fine-tuning
  - Extra fine-tuning adaptors
- Reduce the gap between pre-training and fine-tuning
  - Different pre-training tasks for different downstream tasks
  - Make the data and model consistency with downstream tasks
  - Joint pre-training and fine-tuning

How to use pre-training for downstream tasks?

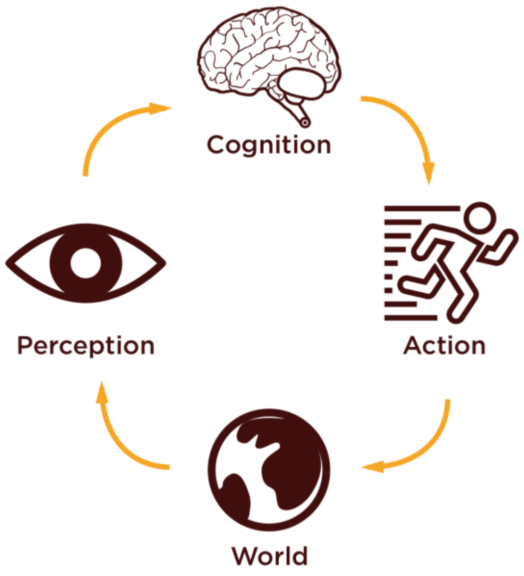
- Different pre-training tasks for different downstream tasks
  - CoLA: The Corpus of Linguistic Acceptability, prefer ELECTRA
  - RTE, MNLI, QNLI: prefer sentence pair pre-training, such as SOP
  - NER: prefer non-degeneration output hidden, BERT instead of ELECTRA
  - SQuAD: prefer span based prediction, span mask
  - NMT, text summarization: prefer seq2seqMLM or conditional sequence generation

How to use pre-training for downstream tasks?

- Compress the pre-trained model for practical deployment
  - Pruning: Compressing BERT [47], LayerDrop [48]
  - Quantization: Q-BERT [49], Q8BERT [50]
  - Parameter sharing: ALBERT[19]
  - Knowledge distillation: DistilBERT [51], TinyBERT [52], LightPAFF [53], BERT-PKD [54], MobileBERT [55], MiniLM [56], DynaBERT [57]
  - Neural architecture search: AdaBERT [58], NAS-BERT [59]

Comparison between pre-trained models for NLP, CV and Speech

- Model size and data size
  - Image: SimCLRv2/800M/300M images, DALL-E/12B/250M image-text pairs,
  - Speech: (Conformer + Wav2vec 2.0)/1B/60K hours speech data
  - NLP: GPT-3/175B/400B tokens → Switch Transformers/1.6 Trillion/180B tokens
- Context-based or Contrast-based?
  - Image, speech, more contrast based
  - NLP, more context-based
- Perception vs Cognition
  - Image, speech is more like perception
  - NLP is more like cognition



Summary of this course

- Overview of pre-training in NLP, CV and Speech
- Taxonomy of self-supervised based pre-training
    - Context based
    - Contrast based
- More discussion about pre-training
    - How to use for down-streaming tasks
    - Comparison between NLP, CV and Speech

Thank You!

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